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Agent Based Modelling and Simulation of Operating Strategies of Generators and Loads in Wholesale Electricity Markets

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All praise be to Allah for his perpetual sustenance and guidance.

May peace and blessings of Allah be upon Prophet Muhammad
and all the previous Prophets who strived for the success of mankind
in this world and the hereafter.

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List of Abbreviations

AMES	Agent-based Modelling of Electricity Systems
APX-ENDEX	Power Exchange for Netherlands and Belgium
ARR	Auction Revenue Rights
CAISO	California ISO
CfD	Contracts for Difference
CRR	Congestion Revenue Rights
DAM	Day-Ahead Market
DC-OPF	DC Optimal Power Flow
EEX	Power Exchange in Germany
EMCAS	Electricity Market Complex Adaptive System
EMTM	Electricity Market Target Model
EPEX	Power Exchange for France and Germany
ERCOT	Electric Reliability Council Of Texas
ERGEG	European Regulators' Group for Electricity and Gas
ERI	Electricity Regional Initiatives
EXAA	Power Exchange in Austria
FABS	Financial transmission instruments, energy Auction and Bilateral transaction Simulator for wholesale electricity markets
FBMC	Flow Based Market Coupling
FBT	Financial Bilateral Transaction
FERC	Federal Energy Regulatory Commission
FTR	Financial Transmission Rights
GenCo	Generation Company
GME	Power Exchange in Italy
IDM	Intra-Day Market
ISO	Independent System Operator
ISONE	ISO New England
LMP	Locational Marginal Price/Pricing

LSE	Load Serving Entity
MASCEM	Multi Agent System that simulates Competitive Electricity Markets
MC	Market Coupling
MCP	Market Clearing price
MIBEL	Power Exchange for Spain and Portugal
MIP	Mixed Integer Programming
MISO	Midwest ISO
MS	Market Splitting
N2EX	Power Exchange in Britain
NEMSIM	National electricity market simulation system
NP	Nord Pool
NYISO	New York ISO
PJM	Pennsylvania-Jersey-Maryland Interconnection
Powernext	Power Exchange in France
PX	Power Exchange
RTM	Real Time Market
RTO	Regional Transmission Operator
SCOPF	Security Constrained Optimal Power Flow
SFT	Simultaneous Feasibility Test
SPP	Southwest Power Pool
TCC	Transmission Congestion Contracts
TSO	Transmission System Operator
WPMP	Wholesale Power Market Platform

List of Mathematical Symbols

A	Risk aversion factor of investor or decision maker
a_g	A coefficient of GenCo g based on actual fuel consumption for Financial Bilateral Transactions [\$/MW^{2}h]
a_g^{Sa}	A coefficient of GenCo g based on actual fuel consumption for price sensitive supply [\$/MW^{2}h]
a_g^{Sr}	A coefficient of GenCo g based on reported fuel cost for price sensitive supply [\$/MW^{2}h]
ap_l^g	Agreed energy price by GenCo g with LSE l [\$/MWh].
ap_g^l	Agreed energy price by LSE l with GenCo g [\$/MWh].
aq_l^g	Agreed power quantity by GenCo g with LSE l [MW].
aq_g^l	Agreed power quantity by LSE l with GenCo g [MW].
ARC_k	Auction revenue credit from ISO for LSE at sink node k.
$ARR_{sk}^{allocated,quantity}$	Allocated Auction Revenue Right quantity between source node s and sink node k [MW].
$ARR_{sk}^{feasible,quantity}$	Feasible Auction Revenue Right quantity between source node s and sink node k [MW].
$ARR_{sk}^{initial,quantity}$	Initial Auction Revenue Right quantity between source node s and sink node k [MW].
$ARR_{sk}^{positive,quantity}$	Positive Auction Revenue Right quantity between source node s and sink node k [MW].
$ARR_{ISO}^{payable}$	ISO’s total anticipated payables to LSEs due to annual ARR allocations
α_l^g	A parameter of GenCo g for estimating maximum strategic price of LSE l by Bayesian learning
b_g	A coefficient of GenCo g based on actual fuel consumption for Financial Bilateral Transactions [\$/MWh]
b_g^{Sa}	A coefficient of GenCo g based on actual fuel consumption for price sensitive supply [\$/MWh]

b_g^{Sr}	A coefficient of GenCo g based on reported fuel cost for price sensitive supply [$/MWh]
B_{oe}	[$1/x_{oe}$] for transmission line oe with origin at node o and end at node e, $oe \in TL$
c_g	A coefficient of GenCo g for actual fixed cost of operation [$/h]
$Cost_g^{FBT}\left(p_g^{FBT}\right)$	GenCo g's cost corresponding to its supply for Financial Bilateral Transactions
$Cost_l^{FBT}\left(p_l^{FBT}\right)$	LSE l's cost corresponding to its load met by Financial Bilateral Transactions
$Cost_l^{I}\left(\lambda_l, p_l^{I}\right)$	LSE l's cost corresponding to its price-inelastic load
$Cost_g^{Sa}\left(p_g^{S}\right)$	GenCo g's actual cost corresponding to its price-sensitive supply
$Cost_l^{S}\left(\lambda_l, p_l^{S}\right)$	LSE l's cost corresponding to its price-sensitive load
$Cost_g^{Sr}\left(p_g^{S}\right)$	GenCo g's reported cost corresponding to price-sensitive supply
$Cost^{Sr}\left(p_G^{S}\right)$	Sum of all GenCos' reported costs corresponding to their price-sensitive supplies
$Cost_g^{Total}$	GenCo g's total cost corresponding to its all supplies
$Cost_l^{Total}$	LSE l's total cost corresponding to its all loads
$CR_l^g\left(t\right)$	Price control ratio of GenCo g, based on estimated maximum strategic price of LSE l in round t.
c_l^S	Coefficient of LSE l for price-sensitive demand [$/MWh]
D_G	Set of standard deviations of LMPs at GenCo nodes
d_l^S	Coefficient of LSE l for price-sensitive demand [$/MW^{2}h]
$\Delta\lambda_{sk}^{act}$	The difference in actual LMPs at source node s and sink node k [$/MWh].
$\Delta\lambda_{sk}^{\exp}$	The difference in overall expectation of LMPs at source node s and sink node k [$/MWh].

δ_1	Reference Node-1 voltage angle (in radians)
δ_n	Voltage angle (in radians) at node n = 2, . . . ,N
$\Delta\pi$	Price interval between discrete price values of negotiable and strategic price sets [$0.1/MWh].
e	Index referring to ending node of a transmission line.
$E(\lambda_g)$	Overall expectation of LMP at local node of GenCo g [$/MWh]
$E(\lambda_i)$	Overall expectation of LMP at node i [$/MWh]
$E(\lambda_k)$	Overall expectation of LMP at sink node k [$/MWh]
$E(\lambda_{ln})$	Overall expectation of LMP at local node ln [$/MWh]
$E(\lambda_s)$	Overall expectation of LMP at source node s [$/MWh]
$E(r_{daa})$, E_{daa}	Expected return from day-ahead auction *daa*
$E(r_{sk})$	Expected return from FTR between nodes s and k
$E(r_g)$	Overall expected return from power trading options of GenCo g.
$E(r_i)$, E_i	Expected return from Financial Bilateral Transaction with market participant (GenCo/LSE) at node i
$E(r_k)$	Overall expected return from FTRs for LSE at node k
$E(r_l)$	Overall expected return from power trading options of LSE l.
$E(r_{lb})$, E_{lb}	Expected return from local Financial Bilateral Transaction lb
E_τ	Expected return from a trading option τ out of the total N+1 trading options.
$FARF_{ISO}$	Feasible ARR reduction factor of ISO.
$Fl_{oe}^{capacity}$	Maximum power flow capacity of transmission line that has origin node o and end node e [MW].
Fl_{oe}^{over}	Over flow of power on transmission line that has origin node o and end node e [MW].

$FQIF_k$	FTR quantity increase factor of LSE at node *k*
$FTR_{sk,\max}^{bid,\text{price}}$	Upper limit of decision variable for bid price optimization between nodes *s* and *k* [$/MW].
$FTR_{sk,\min}^{bid,\text{price}}$	Lower limit of decision variable of LSE for bid price optimization between nodes *s* and *k* [$/MW].
$FTR_{sk}^{bid,\text{price}}$	Price of FTR bid from source node *s* to sink node *k* [$/MW].
$FTR_{sk}^{bid,quantity}$	Quantity of FTR bid from source node *s* to sink node *k* [MW].
$FTR_{sk}^{cleared,price}$	Price of FTR cleared in auction from source node *s* to sink node *k* [$/MW].
$FTR_{sk}^{cleared,quantity}$	Quantity of FTR cleared in auction from source node *s* to sink node *k* [MW].
$FTR_{i}^{held,quantity}$	Financial Transmission Right held by LSE between local node and GenCo node *i*
$FTR_{j}^{held,quantity}$	Financial Transmission Right held by LSE between local node and GenCo node *j*
$FTR_{ISO}^{revenue}$	ISO's total annual FTR auction revenue
GC_{s}^{total}	Total generation capacity at source node *s* [MW].
G	Total number of GenCos
G_k	Set of Generators located at node *k*
$Gn_{g}^{S,\min}$	Minimum real power price-sensitive generation limit for GenCo *g* [MW].
$Gn_{g}^{S,\max}$	Maximum real power price-sensitive generation limit for GenCo *g* [MW].
γ_{ln}	Flat-rate agreed by an LSE with end-consumers at local node *ln*
h	The index refers to a hypothesis in Bayesian learning during bilateral negotiations.
H	Total number of GenCo hypothesis for an LSE's privately

	held maximum strategic price
i	Index referring to one of N nodes.
j	Index referring to a node other than i.
k	Index referring to a sink node.
K	Total number of sink nodes in power system
Ld_k^{base}	Base load at sink node k [MW].
L	Total number of LSEs
$Ld_l^{S,\min}$	Minimum real power price-sensitive load limit for LSE l
$Ld_l^{S,\max}$	Maximum real power price-sensitive load limit for LSE l
L_k	Set of LSEs located at node k
LR_k	Load ratio for load at sink node k.
λ_g	Random variable of LMP at node of GenCo g, irrespective of trading interval z
λ_i	Random variable of LMP at node i, irrespective of trading interval z
λ_j	Random variable of LMP at node j, irrespective of trading interval z
λ_k	Random variable of LMP at sink node k, irrespective of trading interval z
λ_l	Random variable of LMP at node of LSE l, irrespective of trading interval z
λ_{ln}	Random variable of LMP at local node ln of a market participant, irrespective of trading interval z
λ_s	Random variable of LMP at source node s, irrespective of trading interval z
$\lambda_{i,z}$	LMP at node i in trading interval z
$\lambda_{j,z}$	LMP at node j in trading interval z
$\lambda_{k,z}$	LMP at sink node k in trading interval z
$\lambda_{ln,z}$	LMP at local node ln in trading interval z

$\lambda_{s,z}$	LMP at source node *s* in trading interval *z*
μ_{oe}^{+}	Lagrange multiplier of constraint on forward flow of power through transmission line that has origin node *o* and end node *e*.
μ_{oe}^{-}	Lagrange multiplier of constraint on reverse flow of power through transmission line that has origin node *o* and end node *e*.
$\mu_{l,h}^{g}(t)$	A parameter of GenCo *g* based on *h*th hypothesis of LSE *l* in current round *t*
N	Total number of nodes in power system
$np_{l,\max}^{g}$	GenCo *g*’s *maximum negotiable price* for bilateral transaction with LSE *l*
$np_{l,\min}^{g}$	GenCo *g*’*s minimum negotiable price* for bilateral transaction with LSE *l*
N_{l}^{g}	GenCo *g*’s valid *negotiable price set* for bilateral transaction with LSE *l*
$np_{g,\max}^{l}$	LSE *l*’s *maximum negotiable price* for bilateral transaction with GenCo *g*
$np_{g,\min}^{l}$	LSE *l*’*s minimum negotiable price* for bilateral transaction with GenCo *g*
N_{g}^{l}	LSE *l*’s valid *negotiable price set* for bilateral transaction with GenCo *g*
o	Index referring to origin node of a transmission line.
oe	A transmission line (if one exists) with origin node *o* and end node *e*, where $o < e$
p	Index referring to a discrete price in a negotiable or strategic price set.
$PFRF_{ISO}$	Power flow reduction factor of ISO.
p_{g}^{FBT}	Power sold by GenCo *g* against already agreed Financial Bilateral Transaction (FBT) [MW]
p_{g}^{local}	Maximum generation capacity reported to an LSE by its

	local GenCo [MW]
$p_g^{\max}$	Maximum real power generation capacity of GenCo g [MW]
$p_g^{\min}$	Minimum real power generation capacity of GenCo g [MW]
$p_{i,\max}^{FBT}$	Maximum simultaneous feasibility constrained power flow for non-local bilateral trade with market participant (GenCo/LSE) at node i [MW]
$p_{j,\max}^{FBT}$	Maximum simultaneous feasibility constrained power flow for non-local bilateral trade with market participant (GenCo/LSE) at node j [MW]
$p_{i,opt}^{FBT}$	Optimal power quantity allocation for non-local bilateral trade with market participant (GenCo/LSE) at node i [MW]
$p_{j,opt}^{FBT}$	Optimal power quantity allocation for non-local bilateral trade with market participant (GenCo/LSE) at node j [MW]
$p_{i,z}$	Unknown power quantity (that will be allocated by market participant) for bilateral transaction with market participant at node i , in trading interval z [MW]
p_l^I	Price-insensitive real power load of LSE l [MW]
$p_{lb,\max}^{FBT}$	Maximum available power quantity for local bilateral transaction [MW]
$p_{lb,opt}^{FBT}$	Optimal power quantity allocation for local bilateral transaction [MW]
p_l^{base}	Total base load real power requirement of LSE l [MW]
p_l^{local}	Maximum load requirement reported to a GenCo by its local LSE l [MW]
$p_{lb,z}$	Unknown power quantity (that will be allocated by market participant) for local bilateral (*lb*) trading in trading interval z. [MW]
$p_{ln,\max}^{DAA}$	Maximum possible power quantity allocation of a market participant for day-ahead auction at local node ln [MW]

$p_{ln,opt}^{DAA}$	Optimal power quantity allocation of a market participant for day-ahead auction at local node *ln* [MW]
p_{l}^{FBT}	Load requirement of LSE *l* met by already agreed Financial Bilateral Transaction (FBT) [MW]
$p_{ln,z}$	Unknown power quantity (that will be allowed and cleared by ISO) in trading interval *z* at local node (*ln*). [MW]
$Pr^{t}\left(sp_{g}^{l,bid}(t) \mid sp_{l,h}^{g}\right)$	Conditional probability of hypothesis.
$Pr^{t}\left(sp_{l,h}^{g} \mid sp_{g}^{l,bid}(t)\right)$	Posterior probability of hypothesis.
$Pr^{t}\left(sp_{l,h}^{g}\right)$	Prior probability of hypothesis.
$PrDv_{G}^{l}$	LSE *l*'s *price deviation* of price bids to all GenCos
$PrDv_{L}^{g}$	GenCo *g*'s *price deviation* of price bids to all LSEs
p_{g}^{S}	Price-sensitive real power generation (MWs) supplied by GenCo *g*
p_{l}^{S}	Price-sensitive real power load (MWs) demanded by LSE *l*
$PTDF_{oe,sk}$	Power transfer distribution factor for line that has origin node *o* and end node *e* when power flows from source node *s* to sink node *k*.
π_{i}	Assumed price of bilateral contract with market participant (GenCo/LSE) at node i , irrespective of trading interval *z* [$/MWh]
$\pi_{i,z}$	Assumed price of bilateral contract with market participant (GenCo/LSE) at node i , in trading interval *z* [$/MWh]
π_{lb}	Assumed price of local bilateral *lb* contract, irrespective of trading interval *z* [$/MWh]
$\pi_{lb,z}$	Assumed price of local bilateral *lb* contract, in trading interval *z* [$/MWh]
$Q_{l,TOTAL}^{g}$	Total strategic reward of GenCo *g* from bilateral trade with LSE *l*.

$Q_{l,retained}^{g}(t)$	Retained strategic of GenCo g in round t from bilateral trade with LSE l.
$Q_{l,retained}^{g,essential}(t)$	Essential retained strategic of GenCo g in round t from bilateral trade with LSE l.
$Q_{l,retained}^{g,premium}(t)$	Premium retained strategic of GenCo g in round t from bilateral trade with LSE l.
$Q_{l,retained}^{g,prior}$	Prior retained strategic reward of GenCo g at previous price for bilateral trade with LSE l.
$Q_{l,retained}^{g}\left(sp_l^g\right)$	Retained strategic reward of GenCo g at price sp_l^g from bilateral trade with LSE l.
$Q_{g,TOTAL}^{l}$	Total strategic reward of LSE l from bilateral trade with GenCo g.
$Q_{g,retained}^{l}(t)$	Retained strategic reward of LSE l in round t from bilateral trade with GenCo g.
$Q_{g,retained}^{l}\left(sp_g^l\right)$	Retained strategic reward of LSE l at price sp_g^l from bilateral trade with GenCo g.
r_{daa}	Return of day-ahead auction *daa*
r_i	Return of bilateral contract with market participant (GenCo/LSE) at node i
r_{lb}	Return of local bilateral transaction
r_{sk}	Return from FTR between nodes s and k
$r_{s'k}$	Return from FTR between nodes s' and k
$RfPr_g^l$	LSE l's *reference price* for bilateral transaction with GenCo g
$RfPr_l^g$	GenCo g's *reference price* for bilateral transaction with LSE l
$Revenue_g^{FBT}$	GenCo g's revenue corresponding to its supply for Financial Bilateral Transactions
$Revenue_g^{S}\left(\lambda_g, p_g^S\right)$	GenCo g's revenue corresponding to its price-sensitive supply

$Revenue_g^{Total}$	GenCo *g'*s total revenue corresponding to its all supplies
$Revnue_l^{FBT}$	LSE *l'*s revenue corresponding to its load met by Financial Bilateral Transactions
$Revnue_l^I\left(\lambda_l, p_l^I\right)$	LSE *l'*s revenue corresponding to its price-inelastic load
$Revnue_l^S\left(\lambda_l, p_l^S\right)$	LSE *l'*s revenue corresponding to its price-sensitive load
$Revnue_l^{Total}$	LSE *l'*s total revenue corresponding to its all loads
s	Index referring to a source node.
s'	Index referring to a different source node from the source node *s*.
S	Total number of source nodes in power system
S_o	Base apparent power (in three-phase MVAs)
$sp_g^{l,bid}\left(t\right)$	Strategic energy price bid sent by LSE *l* to GenCo *g* in round *t* [$/MWh].
$sq_g^{l,bid}\left(t\right)$	Strategic power quantity bid sent by LSE *l* to GenCo *g* in round *t* [MW].
$sp_l^{g,offer}\left(t\right)$	Strategic energy price offer sent by GenCo *g* to LSE *l* in round *t* [$/MWh].
$sq_l^{g,offer}\left(t\right)$	Strategic power quantity offer sent by GenCo *g* to LSE *l* in round *t* [MW].
$sp_{l,\max}^g$	Maximum value in GenCo *g*'s *strategic price set* for LSE *l* [$/MWh].
$sp_{l,\min}^g$	Minimum value in GenCo *g*'s *strategic price set* for LSE *l* [$/MWh].
$\overset{g}{sp}_{l,\max}\left(t\right)$	GenCo *g*'s estimate of maximum strategic price of LSE *l* in round *t* [$/MWh].
$\overset{g}{sp}_{l,h}$	GenCo *g*'s *h*th hypothesis for maximum strategic price of LSE *l*.
$sp_l^g\left(t\right)$	Strategic price determined by GenCo *g* for LSE *l* in round *t* [$/MWh].
sp_l^g	A valid strategic price of GenCo *g* out of its *strategic price*

	set for bilateral transaction with LSE l S_g^l [$/MWh].
S_l^g	GenCo g's valid *strategic price set* for bilateral transaction with LSE l
$sp_{g,\max}^l$	Maximum value in LSE l's *strategic price set* for GenCo g [$/MWh].
$sp_{g,\min}^l$	Minimum value in LSE l's *strategic price set* for GenCo g [$/MWh].
sp_g^l	A valid strategic price of LSE l out of its *strategic price set* for bilateral transaction with GenCo g S_g^l [$/MWh].
S_g^l	LSE l's valid *strategic price set* for bilateral transaction with GenCo g
$Surplus_l^S\left(p_l^S\right)$	The gross surplus of LSE l corresponding to its price sensitive demand bid
$Surplus^S\left(p_L^S\right)$	Sum of gross surplus for all LSEs corresponding to their price sensitive demand bids
$\sigma^2(\lambda_k)$	Variance of LMP at sink node k
$\sigma^2(\lambda_s)$	Variance of LMP at source node s,
$\sigma^2(\lambda_i)$	Variance of LMP at node i
$\sigma^2(\lambda_{ln})$	Variance of LMP at local node ln
$\sigma(\lambda_g)$	Standard deviation of LMP at local node of GenCo g
$\sigma(\lambda_i)$	Standard deviation of LMP at node i
$\sigma(\lambda_i, \lambda_j)$	Covariance of LMP between nodes i and j
$\sigma(\lambda_{ln}, \lambda_i)$	Covariance of LMP between local node ln and node i
$\sigma(\lambda_{ln}, \lambda_j)$	Covariance of LMP between local node ln and node j
$\sigma(\lambda_k, \lambda_{s'})$	Covariance of LMP between nodes k and s'
$\sigma(\lambda_k, \lambda_s)$	Covariance of LMP between nodes k and s,
$\sigma(\lambda_s, \lambda_{s'})$	Covariance of LMP between nodes s and s'

$\sigma^2(r_k)$	Variance of return from all FTRs to LSE at node *k*
$\sigma^2(r_{sk})$, σ^2_{sk}	Variance of return from FTR between nodes *s* and *k*
$\sigma^2(r_g)$	Overall variance of return from power trading options of GenCo *g*
$\sigma^2(r_l)$	Overall variance of return from power trading options of LSE *l*
σ^2_τ	Variance of return from trading option τ
$\sigma^2(r_{daa})$, σ^2_{daa}	Variance of return from day-ahead auction *daa*
$\sigma^2(r_i)$, σ^2_i	Variance of return from Financial Bilateral Transaction with market participant (GenCo/LSE) at node *i*
$\sigma^2(r_{lb})$, σ^2_{lb}	Variance of return from local bilateral contract
$\sigma_{\tau,\tau'}$	Covariance between returns from trading options τ and τ'
$\sigma(r_i, r_j)$, $\sigma_{i,j}$	Covariance between returns from Financial Bilateral Transaction with market participants (GenCo/LSE)at bilateral contracts at nodes *i* and *j*
$\sigma(r_{lb}, r_i)$, $\sigma_{lb,i}$	Covariance between returns from Financial Bilateral Transactions with market participants (GenCo/LSE) at local node (local bilateral *lb*) and at node *i*
$\sigma(r_{daa}, r_i)$, $\sigma_{daa,i}$	Covariance between returns from day-ahead auction Financial Bilateral Transaction with market participants (GenCo/LSE) at node *i*
$\sigma(r_{sk}, r_{s'k})$, $\sigma_{sk,s'k}$	Covariance of returns from FTR between nodes *s* and *k* and FTR between nodes s' and *k*
t	Index referring to current round of negotiation, where $1 \le t \le T^g$ or $1 \le t \le T^l$
τ	Index referring to one of *N*+1 trading options.
τ'	Index referring to a trading option other than τ .
TA_k^+	Positive target allocations for LSE at sink node *k*.
TA_{total}^+	Total positive target allocations for all LSEs.

TCC_k	Transmission congestion credit from ISO for LSE at sink node *k*.
TCR_{ISO}^{DAM}	ISO's monthly transmission congestion revenue from day-ahead market
TCR_{ISO}^{FTR}	ISO's total monthly transmission congestion revenue from Financial Transmission Rights
TCR_{ISO}^{total}	ISO's total monthly transmission congestion revenue
T^g	Maximum number of rounds for which GenCo *g* is willing to negotiate
T^l	Maximum number of rounds for which LSE *l* is willing to negotiate
TL	Set of all physically distinct transmission lines, a transmission line *oe* has origin node *o* and end node *e*, where $o < e$
$TNC^S\left(p_G^S, p_L^S\right)$	Total net cost corresponding to price-sensitive demand bids and reported price sensitive supply offers
$TNS^S\left(p_G^S, p_L^S\right)$	Total net surplus corresponding to price-sensitive demand bids and reported price sensitive supply offers
U_k	Utility function or objective function of FTR bid price optimization for LSE at node *k*
U_g	Utility function or objective function of portfolio optimization of GenCo *g*
U_l	Utility function or objective function of portfolio optimization of LSE *l*
U_τ	Utility of local bilateral transaction option lb, based on portfolio optimization results
U_i	Utility of bilateral transaction option with market participant at non-local node i, based on portfolio optimization results
U_{lb}	Utility of local bilateral transaction option lb, based on portfolio optimization results

$U_l^g(sp_{l,\min}^g)$	Utility of GenCo *g* from bilateral trade with LSE *l* at minimum value of GenCo's *strategic price* for LSE *l*.
$U_l^g(\pi)$	Utility of GenCo *g* from bilateral trade with LSE *l* at price π.
$U_g^l(sp_{g,\max}^l)$	Utility of LSE *l* from bilateral trade with GenCo *g* at maximum value of LSE's *strategic price* for GenCo *g*.
$U_g^l(\pi)$	Utility of LSE *l* from bilateral trade with GenCo *g* at price π.
V_n	Voltage magnitude (in kVs) at node *n*
V_o	Base voltage (in line-to-line kVs)
$\omega_l^g(t)$	Reward withholding factor of GenCo *g* for LSE *l* in round *t*.
$x_{i,\max}^{FBT}$	Upper limit on portfolio optimization's decision variable for non-local bilateral trade with market participant (GenCo/LSE) at node *i*
$x_{i,opt}^{FBT}$	Optimal value of portfolio optimization's decision variable for non-local bilateral trade with market participant (GenCo/LSE) at node *i*
$x_{j,\max}^{FBT}$	Upper limit on portfolio optimization's decision variable for non-local bilateral trade with market participant (GenCo/LSE) at node *j*
$x_{j,opt}^{FBT}$	Optimal value of portfolio optimization's decision variable for non-local bilateral trade with market participant (GenCo/LSE) at node *j*
$x_{lb,\max}^{FBT}$	Upper limit on portfolio optimization's decision variable for local bilateral (*lb*) trade
$x_{lb,opt}^{FBT}$	Optimal value of portfolio optimization's decision variable for local bilateral trade
$x_{ln,\max}^{DAA}$	Upper limit on portfolio optimization's decision variable for day-ahead auction at local node *ln*
$x_{ln,opt}^{DAA}$	Optimal value of portfolio optimization's decision variable

	for day-ahead auction at local node *ln*
x_{oe}	Reactance (ohms) for transmission line *oe* with origin at node *o* and end at node *e*, $oe \in TL$
x_{τ}	Decision variable of portfolio optimization for fractional allocation of GenCo's *Capacity* / LSE's *Base Load Capacity* to trading option τ .
$x_{\tau'}$	Decision variable of portfolio optimization for fractional allocation of GenCo's *Capacity* / LSE's *Base Load Capacity* to trading option τ' .
$x_{\tau,\max}$	Maximum value for fractional allocation of GenCo's *Capacity* / LSE's *Base Load* to trading option τ .
$x_{\tau',\max}$	Maximum value of for fractional allocation of GenCo's *Capacity* / LSE's *Base Load* to trading option τ' .
z	Index referring to a trading interval
Z	Total number of trading intervals in a decision period for portfolio optimization and historical period for statistical analysis of LMPs.

Abstract

An intelligent agent-based computational approach combined with traditional optimization techniques forms a powerful simulation platform to investigate performance of a wholesale electricity market and behaviour of its participants. Modern deregulated wholesale electricity markets consist of centralized auctions as well as decentralized bilateral transactions. An agent-based system is well suited to model the decentralized aspect of modern electricity markets because various market participants can be represented by autonomous agents. Each market participant has its own private goals and it must learn to survive in a dynamic market environment with incomplete information about other participants.

Majority of existing agent-based simulation models deal with day-ahead auctions but not bilateral transactions. On the basis of available mathematical modelling details for bilateral transactions, agent-based models that can simulate combination of day-ahead auction and bilateral transactions are categorized into simplified models and proprietary software. Although complete mathematical and implementation details of bilateral transactions are publicly available for simplified models, they only represent bilateral transactions facilitated by brokers or bulletin-boards. By comparison, mathematical details of bilateral transactions' models used in proprietary software are not publicly available because of commercial value.

This thesis provides accurate and in-depth understanding of decentralized bilateral transactions by presenting detailed mathematical modelling that includes: (i) match making for bilateral transactions by a systematic direct-search approach and (ii) bilateral negotiations between participants with incomplete information about each other but capability to learn from interactions. The thesis also facilitates wholesale electricity market simulation including the newly developed model for bilateral energy transactions as well as previously existing models of day-ahead energy auction and financial transmission instruments.

1 Introduction

1.1 Research Context

Agent-based modelling is a useful tool to simulate markets to evaluate their performance and behaviour of market participants. Before deregulation, conventional simulation models were adequate representations of centralized decision making for overall optimal operation of an electricity market. Since deregulation, agent-based simulation models have become useful tools for analysing decentralized decision making processes of autonomous market participants. Thus, in agent-based simulation models, generators and demand are modelled as autonomous market participants that have private preferences and goals. In general, an autonomous market participant engages in a number of decentralized decision making processes and this includes securing bilateral transactions as well as determining offers/bids submitted to organized day-ahead auction.

Power Generation Companies and large loads, including Load Serving Entities, participate in a deregulated wholesale electricity market which is managed by an Independent System Operator (ISO). The independent system operator is a non-profit public body whereas the wholesale market participants are private profit-seeking entities. Although both large loads and Load Serving Entities are demand side participants, the focus of this thesis is on Load Serving Entities. In addition, for simplicity it is assumed that each power Generation Company has a single thermal generation unit, while renewable energy resources are not included in modelling.

The independent system operator organises a day-ahead energy auction in order to enable competition among market participants. It has been expected that such competition will help keep wholesale prices in check. The wholesale prices are publicly observable and used as reference for other types of energy trades, including bilateral transactions. However, it is difficult to achieve perfect competition in the electricity market. Thus, the Load Serving Entities face risks of volatile wholesale prices due to imperfect competition and dynamic nature of organised day-ahead energy auction. Similarly, a Generation Company faces risk of potential revenue loss if independent system operator does not find its bids more economical than those of other generators. As a consequence, Load Serving Entities and power Generation Companies may find it beneficial to secure bilateral energy transactions, in advance of day-ahead auction, for hedging risks of price volatility and revenue uncertainty.

In deregulated wholesale electricity markets of USA, bilateral transactions are useful in complementing day-ahead auction because they enable market participants to hedge against uncertain prices and revenues. Since bilateral transactions in USA use historic prices of day-ahead auction as reference, it is helpful to incorporate a model of day-ahead auction for simulation of bilateral transactions in electricity markets of USA.

Bilateral energy transactions can be secured in mainly three ways: (i) through online bulletin-board; (ii) through broker; and (iii) through direct-search, without a bulletin-board or broker. Decision making for bilateral energy transactions consists of two distinct phases. First phase in the decision making is called *match making* and determines suitable trading partners for bilateral energy transactions. In the absence of an organized bulletin-board or broker, each market participant needs to use some kind of a decentralized *match making* mechanism to conduct a direct-search for suitable trading partners. Second phase in the decision making consists of multi-round *bilateral negotiations* for bilateral energy transactions. A successful *bilateral negotiation* leads to a contract specifying agreed quantity and price of energy as well as duration of the contract.

While Generation Companies and Load Serving Entities are free to enter into any trades they wish, a deregulated wholesale electricity market has an underlying physical power system with limited transmission resources to meet dynamic loads. Namely, transmission lines have physical limitations on maximum energy that can flow through the lines from power Generation Companies to Load Serving Entities, while voltages at each of the network buses has to be maintained within specified limits. Therefore, independent system operator must ensure that the power flows, including bilateral energy transactions, do not exceed the maximum limits called *transmission constraints*. In addition to the limited transmission resources, underlying physical power system has limited generation resources at any node and total load requirements are less than total installed generation capacity. As a result of these three limitations, trading opportunities for both Load Serving Entities and Generation Companies are limited. While allowing bilateral energy transactions, the independent system operator must ensure that each market participant has a 'fair and equitable' access to limited system resources. To this end, the independent system operator can announce preliminary maximum levels of simultaneously feasible bilateral transactions that do not violate the 'fair and equitable' access criterion. These maximum levels are preliminary because unforeseen failures of generation or transmission resources and unpredictable load demands can force an independent system operator to curtail bilateral transactions, even if all transactions comply with the preliminary upper limits. Nevertheless, market participants can incorporate the publicly known preliminary upper limits into their decision making for bilateral transactions to reduce risks of curtailments.

If a transmission line happens to carry its maximum possible power flow then *transmission congestion* occurs. In addition, *transmission losses* occur because some power is inevitably wasted as heat while flowing through transmission lines. Due to transmission congestion and transmission losses, organised day-ahead energy auction of a deregulated wholesale electricity market in North America leads to different market clearing prices at different locations, typically referred to as *Locational Marginal Prices*. ISO calculates Locational Marginal Prices by solving optimal power flow problem. Locational marginal prices of power source nodes depend on supply offers of Generation Companies and economic scheduling by ISO. Locational marginal prices of power sink nodes depend on congestion of transmission network. Locational marginal price at a sink node increases if a transmission line transferring power to the node experiences congestion. Load serving entities are responsible for payment of *transmission congestion* costs to independent system operator for power traded by bilateral transactions and in organised day-ahead auction. Transmission congestion costs of a Load Serving Entity due to participation in day-ahead auction are included in Locational Marginal Price at the sink node. Transmission congestion costs of a Load Serving Entity for a bilateral transaction depend on power quantity and difference between Locational Marginal Price at source and sink nodes of the bilateral transaction. Consequently, Load Serving Entities face unpredictable *transmission congestion* costs due to volatile Locational Marginal Prices of organised day-ahead energy auction.

Since the independent system operator is a non-profit public body, it provides a financial instrument so that Load Serving Entities can hedge against their transmission congestion costs. The financial instrument that can hedge transmission congestion costs of Load Serving Entities, due to participation in organised day-ahead energy auction as well as engaging in bilateral transactions is known as *Financial Transmission Rights*. The independent system operator holds an organised annual Financial Transmission Rights auction and Load Serving Entities bid for the Financial Transmission Rights. In addition, the independent system operator provides another financial instrument, *Auction Revenue Rights*, so that Load Serving Entities can hedge against the uncertain cost of acquiring the Financial Transmission Rights at unknown auction clearing prices. The *Financial Transmission Rights* and *Auction Revenue Rights* are collectively called *financial transmission instruments*. Both *financial transmission instruments* are necessary to hedge risks of participation in deregulated wholesale electricity markets. Therefore, when analysing decisions of market participants, it is important to simulate the *financial transmission instruments* in combination with organized day-ahead energy auction and bilateral energy transactions.

Majority of existing agent-based simulation models (including open-source models like [1]) deal with day-ahead auctions but not bilateral transactions. On the basis of available mathematical modelling details for bilateral transactions, agent-based models that can simulate combination of day-ahead auction and bilateral transactions are categorized into simplified models and proprietary software. For simplified models, such as reported in [2], [3] and [4], complete mathematical and implementation details of bilateral transactions' modelling are publicly available in literature. However, without further elaboration, realistic representation of bilateral transactions is acknowledged as future work in [4]. Nevertheless, based on features that are not included in the bilateral transactions model in the referenced paper, this thesis interprets the term “realistic” as follows. Realistic representation of bilateral transactions means *match making* for *direct-search* bilateral transactions by a *systematic* approach and *bilateral negotiations* between participants with *incomplete information* about each other. Mathematical details of bilateral transactions’ models in proprietary software are not made publicly available because of commercial value. Only an overview of implementation techniques is reported for proprietary software, as in [5], [6] and [7].

This thesis aims to build on open-source agent-based software presented in [1] to achieve combined simulation of bilateral energy transactions, day-ahead energy auction and financial transmission instruments. Detailed mathematical modelling of bilateral transactions is provided in this thesis to facilitate accurate and in-depth understanding of implemented model. As an additional advantage, the open-source implementation encourages further extensions in software capabilities by future researchers.

Known simulation techniques for *match making* in electricity markets assume one or more of the following: (i) bilateral transactions are *organized*; (ii) *transmission constraints* do not exist; (iii) participants have *complete information* about other participants; or (iv) *match making* is a random process. One or more of the following deficiencies exist in most previous simulations of *bilateral negotiations*. Use of heuristics, without additional support, can be simplistic or prone to failure of bilateral negotiations. Some learning techniques ignore *dynamic* (varying according to market conditions) prices of organized electricity markets. In case of estimation errors in learning, some learning-dependent adaptation methods can lead to failure of bilateral negotiations.

This research work attempts to achieve simulation of *match making* for *direct-search* bilateral transactions, without requiring any of the assumptions mentioned in above paragraph. Moreover, it demonstrates a new simulation technique for *bilateral negotiations* that can overcome all three deficiencies mentioned in above paragraph. Our research objectives and contributions are outlined in the next two subsections.

The thesis overview and a list of associated publications are presented at the end of this chapter.

1.2 Research Objectives

The overall aim of this research is to improve modelling of decision making for bilateral transactions in deregulated wholesale electricity markets. The overall aim will be achieved through the following set of main and secondary objectives.

1.2.1 Main Objectives

- Design two innovative annual planning methods (one for a Generation Company and the other for a Load Serving Entity) for *match making* in *direct-search* bilateral transactions
- Develop two new computational methods (one for a Generation Company and the other for a Load Serving Entity) to determine optimal dynamic strategies for *bilateral negotiations*; dynamic strategies depend on dynamics of organized day-ahead market during previous year
- Support the computational method of a Generation Company with a novel learning based adaptation method to adjust its dynamic strategies for *bilateral negotiations*; adjustment of dynamic strategies leads to adaptive strategies that depend on observations of opponents' behaviours during current annual bilateral negotiations

1.2.2 Secondary Objectives

- Design a new method for a market participant to determine its optimal bids for submission to *Financial Transmission Rights* auction
- Use existing models of *Financial Transmission Rights* auction and *Auction Revenue Rights* allocation, to manage transmission related risks of Load Serving Entities due to engaging in bilateral transactions and day-ahead auction for energy
- Achieve combined simulation (in an agent-based computational framework) of new decision making models for bilateral transactions and optimization of

bids for transmission rights with existing models for: *Auction Revenue Rights* allocation; *Financial Transmission Rights* auction; and organized day-ahead auction for energy

1.3 Research Contributions

In order to meet the above objectives, this research has made following contributions to existing knowledge pool of agent-based modelling and simulation for deregulated wholesale electricity markets.

- Two new portfolio optimization procedures (one for a Generation Company and the other for a Load Serving Entity); the procedures take into account upper limits, due to *transmission constraints*, on bilateral transactions and availability of *Financial Transmission Rights*
- Two innovative match making algorithms (one for a Generation Company and the other for a Load Serving Entity); the algorithms are capable of systematic *match making* in a decentralized market
- Two new dynamic strategies (one for a Generation Company and the other for a Load Serving Entity) for optimal *bilateral negotiations*; the novel strategies use combination of bilateral transactions' utilities (determined by match making algorithms) and time dependent strategies (determined by current round of multi-round *bilateral negotiations*)
- A novel adaptive strategy to support the dynamic strategy of a Generation Company for *bilateral negotiations*; adaptive strategy depends on estimation, by Bayesian learning, of an opponent's ultimate price based on interactions during current multi-round *bilateral negotiations*
- A new method to determine optimal bids of a market participant for submission to *Financial Transmission Rights* auction
- Achieved agent-based combined simulation of annual Financial Transmission Rights auction and annual Auction Revenue Rights allocation along with annual bilateral transactions and organized day-ahead market for energy

1.4 Thesis Overview

The rest of the thesis chapters have following layout.

Chapter 2 – this chapter presents a review of wholesale electricity markets in North America and the Europe. It highlights overall common characteristics of wholesale electricity markets in both continents. The chapter also explains differences in details of market designs for both continents. The market comparison covers five dimensions: common characteristics, general aspects, generation scheduling, transmission arrangements and bids processing.

Chapter 3 – presents a review of simulation models and techniques for wholesale electricity markets. This chapter discusses some game-theoretic equilibrium models followed by a review of agent-based simulation models for electricity markets. It also explores learning and optimization techniques for specific operational problems of individual market participants which can contribute to overall simulation of an electricity market.

Chapter 4 – this chapter presents a summary description of *simulated electricity market* in this thesis. It outlines model of the *simulated electricity market* with reference to market operations in real world electricity markets. This chapter discusses sequence of events in the *simulated electricity market.* Reasons for choosing specific simulation and machine learning techniques for the *simulated electricity market* are also discussed in this chapter.

Chapter 5 – presents *Auction Revenue Rights* allocation and *Financial Transmission Rights* auction in details. Complete mathematical models of *Auction Revenue Rights* allocation and *Financial Transmission Rights* auction are provided. The chapter also includes a new risk-constrained method to optimize bidding prices of Load Serving Entities in *Financial Transmission Rights* auction.

Chapter 6 – this chapter discusses portfolio optimization procedures of Generation Companies and Load Serving Entities. Complete mathematical models of portfolio optimization procedures are explained in detail.

Chapter 7 – this chapter discusses how portfolio optimization procedures are used in match making algorithms of Generation Companies and Load Serving Entities for *direct-search* bilateral transactions. It also explains how results of portfolio optimization procedures are used to determine utilities of bilateral transactions over a range of prices.

Chapter 8 – a *bilateral transaction protocol* for *direct-search* bilateral transactions is described in this chapter. Furthermore, the chapter discusses how Generation Companies and Load Serving Entities use results of match making algorithms to develop dynamic strategies for bilateral negotiations over a range of prices. In addition, it is explained how Generation Companies use Bayesian learning to develop adaptive strategies to adjust their responses during *bilateral negotiation*.

Chapter 9 – simulation results for aspects covered in Chapter 5 to Chapter 9 are provided within respective chapters. This chapter presents main conclusions of this research and offers insights into future research dimensions.

1.5 Associated Publications

- K. Imran and I. Kockar, "A technical comparison of wholesale electricity markets in North America and Europe," Electric Power Systems Research, vol. 108, pp. 59-67, 2014.
- K. Imran, Y. Zhao, and I. Kockar, "Simulation of Portfolio Optimization by Electricity Trading Participants in a Multi-agent System," accepted for presentation at the European Energy Market (EEM), 2014 11th International Conference on the, 2014. The paper could not be presented due to visa delays and has now been submitted to 12th Intelligent Systems Applications to Power Systems Conference 2015.
- K. Imran and I. Kockar, "A risk-constrained bid optimization method for Financial Transmission Rights auction," *Power Systems, IEEE Transactions on,* in preparation for submission in 2015.

- K. Imran and I. Kockar, "A portfolio optimization method for generators in electricity markets," *Power Systems, IEEE Transactions on*, in preparation for submission in 2015.
- K. Imran and I. Kockar, "A portfolio optimization method for loads considering Financial Transmission Rights," *Power Systems, IEEE Transactions on*, in preparation for submission in 2015.
- K. Imran and I. Kockar, "Decentralized match making for bilateral transactions between generators and loads by direct search," *Power Systems, IEEE Transactions on*, in preparation for submission in 2015.
- K. Imran and I. Kockar, "Utility-based bilateral negotiations between generators and loads supported by Bayesian learning," *Power Systems, IEEE Transactions on*, in preparation for submission in 2015.

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2 Wholesale Electricity Markets: A Technical Comparison of North American and European Market Designs

2.1 Introduction

It is imperative to know characteristics of real world market operations which can serve as criteria to determine suitability of existing simulation models and techniques for wholesale electricity markets. These will be referred to as criteria characteristics of wholesale electricity market simulation. Secondly, it is critical to examine the extent of implementation differences in wholesale electricity markets' mechanisms in North America and Europe. This examination will determine whether simulation models of markets in one continent, e.g. North America, can be used for simulation of markets in the other continent, i.e. Europe. This chapter seeks to establish *criteria characteristics* and extent of implementation differences in wholesale electricity market mechanisms of the two continents. However, since this thesis restricts to current wholesale electricity markets, study of retail electricity markets and comprehensive history of wholesale markets' restructuring is beyond its scope. An account of lessons learned from electricity market liberalization in various parts of the world is reviewed in [1].

As discussed in Chapter 1, power Generation Companies (GenCos) and Load Serving Entities (LSEs) participate in a deregulated wholesale electricity market. An independent system operator has overall control of the deregulated market but allows bilateral transactions between participants. Participants can privately agree on energy prices of their bilateral transactions. In addition to allowing bilateral transactions, the independent system operator arranges organized energy trades for market participants. For the organised trades, independent system operator collects energy offers from power Generation Companies and demand bids from Load Serving Entities to conduct an auction of energy. The independent system operator also receives power quantities of bilateral transactions agreed between market participants. On the basis of information submitted by market participants, the independent system operator clears the auction for organised energy trades and determines power quantities of bilateral transactions that can be transferred by available transmission resources. Purposes and methods of bilateral transactions and organized trades are described as follows.

Participants of organized markets face risks of price volatility and revenue uncertainty. However, participants can hedge these risks by securing bilateral energy transactions in advance of the organized markets. It is crucial to note that energy prices in day-ahead markets serve as reference prices for Financial Bilateral Transactions in electricity markets of USA [2] and EU [3]. In addition, bilateral transactions are highly preferred by market participants because they avoid exposure to pool liquidity risks [4]. Following classification and discussion on bilateral transactions is neither absolute nor exhaustive. However, it reasonably elaborates meanings and types of bilateral transactions for the purposes of this thesis.

Bilateral transactions can be reached through brokers, online bulletin-boards or by direct-search that does not need a broker or a bulletin-board. Bilateral transactions by direct-search and through broker are secured in two phases. The first phase is called *match making* and the second phase is called *bilateral negotiations*. However, online bulletin-board facilitates bilateral transactions by *match making* only.

According to mode of delivery of energy, bilateral transactions can be divided into physical and financial bilateral transactions. A *physical bilateral transaction* is a contract for transfer of energy (by the physical flow of energy) between a buyer and a seller. A *financial bilateral transaction* is a contract for transfer of financial responsibility for energy (not the physical flow of energy) between a buyer and a seller. Physical and financial bilateral transactions are further discussed in this Chapter in next sections.

Bilateral transactions of long duration (from five to ten years) are used to support the development of new energy resources. Bilateral transactions of medium duration (from six months to five years) are useful to hedge risks of price volatility and revenue uncertainty. Both long and medium duration bilateral transactions are privately reached by direct-search in a decentralized manner. Decentralized decision making for both long and medium duration bilateral transactions involves two distinct phases called *match making* and *bilateral negotiation*. Long and medium duration bilateral transactions are customized for private needs of participants. Both types of bilateral transactions depend on long term load forecast and can involve hundreds of MWh of energy.

In addition to hedging risks of price volatility and revenue uncertainty, bilateral transactions of short duration (from one month to six months) are useful to make up for any medium term bilateral transactions that could not be agreed due to negotiation failure. Short duration bilateral transactions are also helpful in adjusting trading requirements in view of short term load forecast. Short duration bilateral transactions take place in an organized manner through broker or via online bulletin-board. Match making phase of decision making for short duration bilateral transactions is organized by a human broker or software underlying online bulletin-board. Bilateral negotiations may be necessary in case of match making by a broker. However, match making by online bulletin-board is binding on participants and does not require subsequent bilateral negotiations. Short duration bilateral transactions can involve tens of MWh of energy and are standardized contracts for different peak and off peak times of a day and/or week.

In general, bilateral transactions are based on load forecasts that may not match with actual load requirements and unpredictable faults may cause a generating unit to shut down or curtail its output in real time. Furthermore, participants may not be able to secure bilateral transactions for their full forecasted loads or generation capacities. Independent system operator is responsible for balancing generation with demand in real time. Organized trades allow Load Serving Entities to fulfil their actual load requirements and Generation Companies to competitively offer their full generation capacities. Moreover, organized trades enable the independent system operator to balance generation and demand in real time and consequently maintain reliability of power system operation.

Therefore, since the deregulation of electricity sector, a number of approaches to organization of electricity markets, trading and charging methodologies emerged. Comparing these approaches is often difficult due to new developments, as well as the practice in which details about market design are often embedded in a multitude of documents on various websites of system operators. This chapter is adopted from our research paper [5] which was written to help researchers looking into the different approaches. The paper presented a comparison of prevailing market design of the USA with market in Nordic countries as well as emerging market coupling in Europe. The market in Nordic countries, Nord Pool, is separately considered in the comparison because it shares some characteristics of markets in the USA and others of the remaining European markets. As mentioned above, the comparison in [5] fulfils one aim of this chapter, i.e. to establish extent of implementation differences in wholesale electricity market mechanisms of the two continents. Here the comparison presented in [5] is supplemented by discussion which aims to establish *criteria characteristics*. The next two paragraphs are devoted to the markets to be compared in this review.

North American electricity markets are among the most mature electricity markets in the world today. Types of energy markets, ancillary services for balancing and reserves markets, bilateral trades and financial transmission instruments of a number of electricity markets in North America are compared here including those in the states of New York (NYISO), New England (ISONE), California (CAISO) and Texas (ERCOT). Pennsylvania-Jersey-Maryland (PJM) Interconnection and Midcontinent Independent System Operator (MISO), two other important markets in North America that cover multiple states, are included in the comparison. An overview of status of wholesale markets in the rest of the USA is also included in this comparison.

Evolution of electricity markets in Europe is leading to emerging electricity market coupling of day-ahead markets of different countries. Wholesale electricity markets of sixteen European countries including Norway, Sweden, Finland, Denmark, Estonia, Germany, France, Spain, Portugal, Britain, Ireland, Netherlands, Luxembourg, Belgium, Austria and Italy are covered here. In addition, power exchanges of Nord Pool (Nordic Countries and Estonia), N2EX (Britain), MIBEL (Spain and Portugal), GME (Italy), APX-ENDEX (Netherlands and Belgium), Powernext (France), EEX (Germany), EPEX (France and Germany) and EXAA (Austria) have been compared and explored for existence of physical markets (auction or continuous trading) and financial markets (futures for base or peak load). In addition, bilateral trades are supported to complement above mentioned organized markets.

Rest of this chapter is structured as follows. First, prevailing design of wholesale electricity markets in the USA is discussed in Section 2.2, while Section 2.3 covers emerging electricity market coupling in the EU. Overview, energy trading mechanisms and transmission arrangements of the two market designs are presented under the respective headings in Sections 2.2 and 2.3. Section 2.4 is divided into two parts that correspond to the two aims of this chapter. Section 2.4.1 discusses *criteria characteristics* of wholesale electricity markets in both continents, while Section 2.4.2 covers extent of implementation differences in mechanisms used in wholesale electricity markets of the two continents. It includes a detailed comparison of market designs of the USA and the EU. Three aspects are covered in the section including (i) general comparison, (ii) energy trading mechanisms and (iii) transmission arrangements. Details of the three aspects covered in Section 2.4.2 are presented in the next paragraph.

Firstly an overall general comparison of prevailing wholesale electricity market designs in Europe and North America includes aspects like market model, asset ownership, interaction of transmission and market operators and relative volumes of day-ahead auction market and forward bilateral trades. Secondly, a comparison of energy trading mechanisms in both continents is provided. This includes nature of generators operations, structure and data involved in generator bidding and extent of self-scheduling of generation in the two continents. It also covers optimization procedures and underlying concepts used in processing of bids and resulting zonal/nodal or linear/non-linear pricing. Finally a comparison of transmission arrangements discusses degree to which network constraints are taken care of. The comparison also covers transmission capacity allocation and calculation methods for forward bilateral trades and day-ahead market.

2.2 Prevailing Design of Electricity Markets in the USA

2.2.1 Overview

Federal Energy Regulatory Commission (FERC) of USA issued a standard market model called Wholesale Power Market Platform in 2003 to be commonly adopted by all wholesale power markets in the USA. Accordingly, this model has been adopted, with some subtle differences, by a majority of Independent System Operators (ISO) and/or Regional Transmission Operators (RTO) in the USA. In essence, Wholesale Power Market Platform consists of a number of markets run by an ISO/RTO. These markets include organized energy markets, ancillary services markets (for balancing and reserves) and Financial Transmission Rights markets (for hedging transmission congestion costs). In addition, bilateral energy transactions are allowed between market participants. Wholesale Power Market Platform includes some mechanisms such as capacity markets to ensure resource adequacy for future by ensuring investment in new generation. However, resource adequacy measures or capacity markets greatly vary among different regions and are not part of discussion in this chapter.

Energy markets have two components: a real-time market called Spot, and a day-ahead market called Forward. In the case of ancillary markets for balancing and reserves, real-time market and day-ahead market are typically called Regulation and Reserve respectively. However, there are some differences in precise names of markets which are dealing with balancing and reserves for different regions. It is important to point out that Financial Transmission Rights can hedge market participants against risks of *transmission congestion* and resulting costs. The Financial Transmission Rights are useful to hedge against *transmission congestion* costs arising from energy trading through both organized energy markets and bilateral energy transactions.

ISOs/RTOs of North America are shown in a map in Figure 2.1 whereas Table 2.1 (modified from [6]) gives an overview and comparison of market structures in these ISOs/RTOs. It is important to note that most of the West of the USA (excluding California) and the South East do not have ISO or RTO. In fact, in both of these regions, energy is traded by bulk decentralized bilateral transactions that are complemented by some centralized real time balancing. Southwest Power Pool (SPP) is in transition from purely bilateral trades to some version of Wholesale Power Market Platform. Electric Reliability Council of Texas (ERCOT) has implemented nodal pricing system that replaced the previous zonal pricing regime so it has also adopted Wholesale Power Market Platform [7].

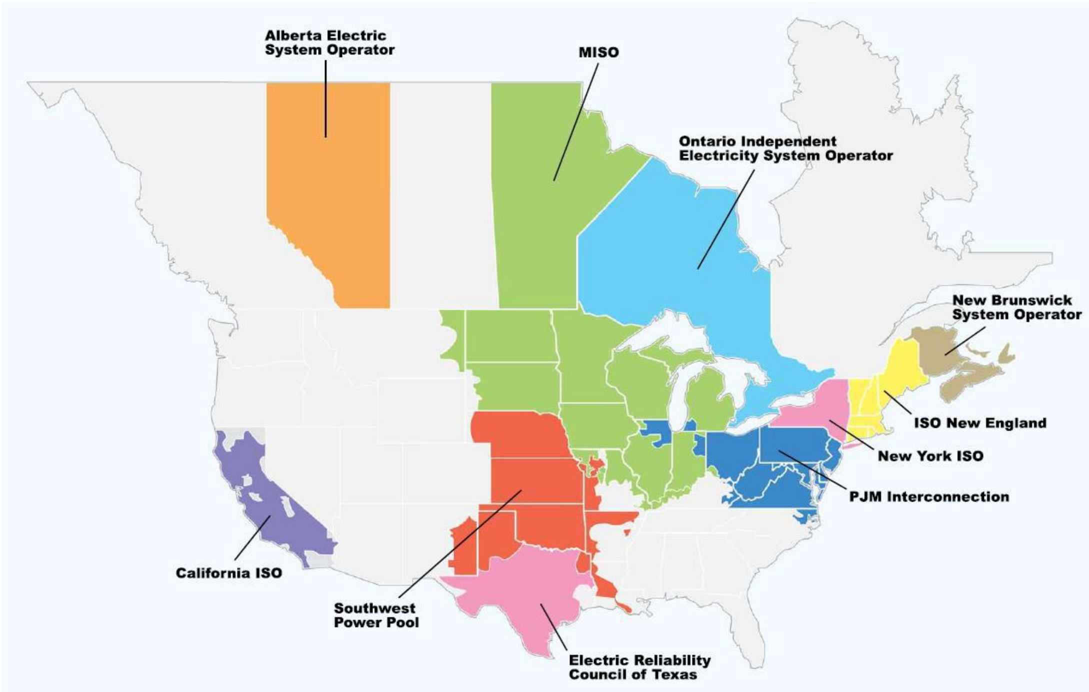

Figure 2.1 A Map of ISOs/RTOs of North America (Source: ISO/RTO Council, Copyright © ISO/RTO Council, all rights reserved)

Table 2.1 Overview of Wholesale Electricity Markets of North America

Grid Operator	**Energy Markets**		**Ancillary Services Markets**		**Bilateral Transactions**		**Financial Transmission Instruments**	
Independent System Operator	Real-time Market (Spot)	Day-ahead Market (Forward)	Real-time Market (Regulation)	Day-ahead Market (Reserve)	Physical	Financial	FTR	ARR
ISONE	✓	✓	✓	✓	✓	✓	✓	✓
MISO	✓	✓	✓	✓	✓	✓	✓	✓
PJM	✓	✓	✓	✓	✓	✓	✓	✓
NYISO	✓	✓	✓	✓	✓	✓	✓	
CAISO	✓	✓	✓	✓	✓	✓	✓	
ERCOT	✓	✓	✓	✓	✓	✓	✓	
SPP	✓				✓			
West (outside CAISO); the Southeast					✓[1]			

[1] These markets have a real time central balancing mechanism to complement decentralized bilateral trades

2.2.2 Energy Trading Mechanisms

In the USA, market participants have a number of options for interacting in ISO organized pools that follow Wholesale Power Market Platform. For example, energy trading mechanisms in MISO, described in [8], allow market participants to have a number of options for participating in the day-ahead energy market. Before describing the trading options it is important to define a few relevant terms here. A *physical schedule* is an option to participate in day-ahead market to transfer the energy (by the physical flow of energy) between a buyer and a seller. For a *physical schedule*, GenCo and LSE can bilaterally settle energy price but need a prior confirmation of physical transmission reservation between GenCo (source) and LSE (sink) node. A *financial schedule* is an option to participate in day-ahead market to transfer the financial responsibility for energy (not the physical flow of energy) between a buyer and a seller. The independent system operator considers GenCos' *price-sensitive supply offers* and LSEs' bids to determine most economical (on the basis of data provided in offers) operating schedules of generation units - *offer-based economic schedules*. A *self-schedule* is an option to participate in day-ahead market which allows a generator to run at least at the self-schedule level as a "price-taker". In addition, a GenCo (LSE) can hedge against changes in LMP between the day-ahead and real-time energy markets by submitting a *virtual demand bid* (*virtual supply offer*) that is not necessarily supported by any physical load demand (generation resource). MISO participants can use any combination of the following trading options.

i. Physical schedules to fulfil requirements of physical bilateral transactions
ii. Financial schedules to fulfil requirements of Financial Bilateral Transactions.
iii. Power generation bids for selling energy in day-ahead auction at variable market clearing prices by *offer-based economic schedules* or *self-schedules*.
iv. Power demand bids for buying energy in day-ahead auction at variable market clearing prices or at "not-to-exceed" prices.
v. Virtual supply offers and demand bids to fulfil required hedge against the LMP changes

In MISO different types of physical and Financial Bilateral Transactions are allowed. Grandfathered Agreement Carve Out Transactions are physical bilateral transactions that are allowed within MISO. They existed before creation of MISO and were allowed by Federal Energy Regulatory Commission to be carved out of MISO markets [9]. Grandfathered Agreement Carve Out Transactions can be achieved as follows. After GenCo and LSE declare a physical bilateral transaction, GenCo requests a *physical schedule* from the system operator, and LSE directly pays GenCo for energy. Since LSE holds a non-billable (free of cost) transmission service reservation, it avoids payment to ISO for the *physical schedule* of energy over transmission network [9].

On the other hand, in the case of Financial Bilateral Transactions in MISO, GenCo and LSE declare a Financial Bilateral Transaction and GenCo requests a *financial schedule.* The GenCo is allowed to inject power into transmission network so that it can at least provide energy for the *financial schedule* but LSE has to pay ISO for transmission congestion and losses, according to difference of LMPs at sink and source nodes of the *financial schedule.* ISO may reduce financial, physical and self-schedules under exceptional circumstances; some examples of the exceptional circumstances are discussed in coming paragraphs. The energy price of the *financial schedule* is bilaterally settled out of MISO. Moreover, if LSE holds FTRs then the transmission congestion cost can be fully hedged.

When a generator submits its whole generation for *offer-based economic schedules* by MISO, it can be "price-setter" for the Locational Marginal Price at its local node. However, when a generator chooses to *self-schedule* its whole generation then it only operates as a "price-taker" [10]. As a middle case, generator may *self-schedule* part of its generation and offer the remaining capacity for *offer-based economic schedule* by MISO. In this case, the generator is allowed to run at least at the *self-schedule* level but ISO determines price paid to the generator for the *self-schedule.* MISO may choose *offer-based economic schedule* for remaining capacity of the generator if its offer is considered more economical than other generators.

A generator may find whole or partial *self-schedule* beneficial for a number of reasons. For example, a market design may not allow out of market settlement for energy traded by bilateral transactions. In such a case a *self-schedule* will allow a GenCo to participate in market as a "price-taker". After market settlements with ISO at market clearing prices, GenCo and LSE will be able to settle their differences according to a bilaterally agreed *contract-for-difference*. If an LSE can fully hedge congestion risk by holding FTR to cover the agreed transaction volume then a *self-schedule* and *contract-for-difference* combination works as a perfectly hedged bilateral transaction [4] [11].

However, a generator may be forced to *self-schedule* due to mechanical or other reasons. For instance, a generator may have a take-or-pay fuel contract such that it has to pay for fuel even if it does not take its fuel supply. In this case a generator may opt for *self-schedule* to avoid loss of fuel payment. Sometimes, parent company of a generator may also be serving some own loads and may choose to *self-schedule* the generator to cater for own loads (self-supply).

After receiving offers of generators and bids of loads, the MISO runs a pool clearing algorithm which automatically accepts *physical schedules*, *financial schedules* and *self-schedules* subject to transmission constraints. Then, the ISO issues all accepted schedules including *offer-based economic schedules* as well as feasible *physical schedules*, *financial schedules* and *self-schedules*. According to [8], MISO may have to reduce accepted *self-schedules* for power system management under certain circumstances. For example, the reduction may be necessary to manage unpredictable transmission failures or maintain system reliability. MISO may also need to reduce accepted *physical schedules* and *financial schedules* due to similar reasons.

There are conflicting opinions regarding relative volumes of bilateral transactions and organized markets in the deregulated electricity markets of USA. For example, [12] claims that bilateral transactions exceeded 90% of real-time energy market load of PJM in 2006. However, the claim is contested in [2] as explained next. In addition to GenCos and LSEs, energy marketers also participate in PJM who purchase energy in wholesale market and sell it to some LSEs in the retail market. While some LSEs directly purchase from the real-time energy market, others buy from the marketers. Only if an LSE directly buys from the real-time energy market then it is classified as a non-bilateral transaction by [12]. However, if a marketer buys from the real-time energy market then it is categorized as a bilateral transaction by [12], whereas it is not a wholesale bilateral transaction between a GenCo and a marketer. It is claimed in [2] that relatively few bilateral transactions are used in deregulated wholesale electricity markets. However, according to [4] most trading in deregulated wholesale electricity markets, indeed, occurs bilaterally. This view is supported by data for NYISO where bilateral trades make-up 50% of scheduled energy whereas 48% is traded in day-ahead market and only 2% in real-time market [13].

Due to confidential nature of bilateral transactions, it is not easy to determine the overall volume of bilateral transactions as compared to organized markets in the deregulated electricity sector of USA. According to the 2010 annual market report for ISONE [14], out of total cleared supply, 60% were self-schedules, 26% were price-sensitive supply offers, 4% were virtual supply offers and 10% were imports. The 26% trading by price-sensitive supply offers must be counted as organized market trading. On the other hand, imports make up 10% that are clearly physical bilateral transactions between participants located in different markets. The *self-schedules* and *virtual supply offers* add up to 64% of the total trades. Some *self-schedules* and *virtual supply offers* may be serving bilateral transactions but the annual reports do not provide any further breakup of these two types of trades. In fact limited data is publicly available on bilateral transactions [2], for instance, generators *self-schedule* to fulfil some bilateral transactions but they do not have to declare such bilateral transactions.

2.2.3 Transmission Arrangements

A Financial Transmission Right (FTR) is a financial instrument that does not entitle its holder to a physical right for power delivery. Financial Transmission Rights can be obligation FTRs or option FTRs. An obligation FTR holder can be either entitled to a payment for congestion credits or liable to a payment of congestion charges. On the other hand, an option FTR holder may be entitled to congestion credits but not liable to congestion charges. Difference between LMPs at the sink and source nodes of an FTR determines whether FTR holder gets credits or incurs charges. If LMP at the sink node is higher than LMP at the source node then obligation/option FTR holder gets congestion credits. Otherwise, obligation FTR holder incurs congestion charges but option FTR holder avoids any congestion charges. An FTR payment equals the product of the MW amount for which FTR is obtained (through auctions) and the differences in the congestion component of LMPs at the agreed source and sink points [15], [16]. Annual and monthly auctions of FTRs or equivalent instruments exist in all markets that now follow some version of Wholesale Power Market Platform. However, number of auction rounds and percentage transmission capacities sold in annual and monthly auctions vary among these markets. Financial instruments equivalent to FTRs are called Congestion Revenue Rights (CRR) in CAISO [17] and ERCOT [18], whereas in NYISO, the financial instruments are known as Transmission Congestion Contracts (TCCs) [19].

Auction Revenue Rights (ARRs) are another category of financial instruments that allow holders to get a share of revenue from Annual FTR Auction. ARRs are used in addition to FTRs in PJM [16], MISO [20] and ISONE [15]. In fact ARRs are allocated, unlike FTRs that are auctioned, to participants on the basis of their historical usage of the transmission network. In addition, Incremental ARRs are allocated to those participants who fund network upgrades or build new/replacement resources for network [20]. Consequently, Incremental ARRs act as a crucial instrument that ensures adequate upgrading and expansion of transmission grid. Alternatively, ISO can undertake appropriate grid expansions/upgrades and can allocate costs to market participants. In 2011 Federal Energy Regulatory Commission issued Order 1000 as a final rule on transmission planning and cost allocation. The Order stipulates that transmission owning and operating public utilities are responsible for transmission planning and cost allocation. It requires regional transmission planning should consider and evaluate possible alternatives and then fairly allocate cost of chosen transmission solution among beneficiaries [21].

Annual allocations of ARRs or equivalent instruments exist in all markets that now follow some version of Wholesale Power Market Platform. However, number of stages or procedures of allocations vary among these markets.

2.3 Emerging Electricity Market Scenario in the EU

2.3.1 Overview

European Regulator's Group for Electricity and Gas (ERGEG) launched the 'Electricity Regional Initiatives' in 2006 and established seven regional initiatives in Europe, shown in Figure 2.2. The Electricity Regional Initiatives were designed with the ultimate goal of a pan-European electricity market. This envisioned Europe-wide market is termed Electricity Market Target Model in this chapter and it revolves around the idea of Market Coupling.

Figure 2.2 A Map of Electricity Regional Initiatives of Europe (Source: Edited from online blank map and inspired by Electricity Market Coupling Company)

There are two basic types of market coupling called volume coupling and price coupling. If power exchanges have volume coupling then they forward received bids and offers to a central coupling algorithm that calculates trading volumes but leaves price calculations for power exchanges. In case of price coupling, the coupling algorithm determines both prices and volumes of trades. It is possible to achieve volume coupling by coordinated utilization of available interconnection capacity. On the other hand, price coupling is more comprehensive because it combines price and volume coordination across borders [22] and [23].

Most Electricity Regional Initiatives have made some progress in integrating markets within region covered by each Electricity Regional Initiative. For example, in the Electricity Regional Initiative for Northern region, Nord Pool Spot (NPS) was established in 2002 as a separate company to cover Denmark, Norway, Sweden and Finland. Then, in November 2009, volume coupling was launched by Electricity Market Coupling Company that linked Nord Pool Spot with the European Power Exchange (EPEX) in Germany.

As another example, Tri Lateral Coupling of markets in France, Belgium and the Netherlands was established in 2006 (by price coupling) within the Electricity Regional Initiative for Central-West Europe. In November 2010, price coupling was achieved throughout the Electricity Regional Initiative for Central-West Europe that covered France, Belgium and the Netherlands (previously Tri Lateral Coupling) as well as Germany, Luxembourg and Austria.

The next phase to progressively couple these Electricity Regional Initiatives together is already underway. In November 2010, at the same time as introduction of price coupling throughout Central-West Europe, volume coupling was initiated between Central-West Europe market and Nordic market. The volume coupling was termed Interim Tight Volume Coupling because of following reasons. It was called interim coupling because it was a temporary arrangement and all participants agreed to eventually achieve price coupling. It was known as tight coupling because the market coupling algorithm accurately simulated clearing processes of the linked power exchanges [24]. It is important to note that day-ahead markets have been coupled as a first step as discussed above. However, work is also in progress to couple intraday markets and on some borders, like France-Germany and Netherlands-Belgium, the intraday markets have already been coupled [25].

Electricity Market Target Model consists of four basic components, as presented in [26], namely forward market, day-ahead market, intraday market and balancing. It is important to note that forward market and balancing are run by Transmission System Operators (TSOs) whereas day-ahead market and intraday market are organized by power exchanges. In addition, power exchanges arrange futures market which is financial counterpart of forward market. Electricity market participants can obtain transmission capacity for their trades in two ways. If a TSO exclusively holds an auction for transmission capacity then it is termed explicit auction. It is anticipated by Electricity Market Target Model that forward market will continue to use explicit auction held by TSOs for transmission capacity. When a power exchange clears its auction for energy then transmission capacity for cleared energy trades is automatically allocated – implicit auction. In Electricity Market Target Model, power exchanges will use implicit auction in day-ahead market and implicit continuous trade in intraday market. In some European power exchanges, intraday continuous trading can be categorised as spot or prompt. Spot trading covers blocks of half hourly, hourly, two hourly and four hourly trades and their combinations whereas continuous prompt trading includes trades like peak hours, base load, weekend and overnight. Balancing will be achieved on the basis of a common merit order by trading between neighbouring TSOs [25].

An overview of power exchanges in the Europe is presented in Table 2.2. Interestingly, Britain is the only country to have as many as three power exchanges simultaneously operating with overlapping physical and financial markets. In the rest of Europe, a maximum of two power exchanges are operational and even these cater for either physical or financial trading. Developments due to Electricity Regional Initiatives have led to mergers, joint ventures and cooperation among countries in the same region often resulting in a financial market in one country and its physical counterpart in the neighbouring country. In case of Spain-Portugal, joint power exchange MIBEL runs two markets called OMIE and OMIP; OMIE (Spain) handles physical trades and OMIP (Portugal) deals with financial trades for both countries.

As another example, EPEX (Germany) caters physical trading and EEX (France) facilitates financial trading for both France and Germany.

In addition to above described markets for energy, some power exchanges offer trading of financial instruments to manage costs of transmission congestion and carbon emissions. Contracts for Difference in Nord Pool are financial instruments, like commonly used FTRs in the USA markets, for hedging against risk of transmission congestion. Moreover, introduction of EU Emissions Allowances has resulted in carbon markets in EEX Germany and NASDAQ OMX in Nord Pool. It is anticipated that more power exchanges will offer carbon trading as EU moves from free allocation to auctioning of the emissions allowances.

Table 2.2 Overview of Wholesale Electricity Markets of the Europe

<table>
<tr><th rowspan="3">Country</th><th rowspan="3">Power Exchange</th><th rowspan="3">Markets</th><th colspan="3">Physical Trading</th><th colspan="2">Financial Trading</th></tr>
<tr><th>Day-ahead</th><th colspan="2">Intra Day Continuous</th><th colspan="2">Futures</th></tr>
<tr><th>Auction</th><th>Spot</th><th>Prompt</th><th>Base</th><th>Peak</th></tr>
<tr><td rowspan="4">Britain</td><td rowspan="2">APX-ENDEX</td><td>APX Power UK</td><td>✓</td><td>✓</td><td>✓</td><td></td><td></td></tr>
<tr><td>ENDEX Power UK</td><td></td><td></td><td></td><td>✓</td><td>✓</td></tr>
<tr><td>N2EX</td><td>N2EX</td><td>✓</td><td>✓</td><td>✓</td><td colspan="2">✓</td></tr>
<tr><td>ICE</td><td>ICE</td><td></td><td></td><td></td><td>✓</td><td>✓</td></tr>
</table>

<table>
<tr><th rowspan="3">Country</th><th rowspan="3">Power Exchange</th><th rowspan="3">Markets</th><th colspan="3">Physical Trading</th><th colspan="2">Financial Trading</th></tr>
<tr><th>Day-ahead</th><th colspan="2">Intra Day Continuous</th><th colspan="2">Futures</th></tr>
<tr><th>Auction</th><th>Spot</th><th>Prompt</th><th>Base</th><th>Peak</th></tr>
<tr><td rowspan="2">Nordic Countries[2]</td><td rowspan="2">NP</td><td>NPS</td><td>✓</td><td colspan="2">✓</td><td></td><td></td></tr>
<tr><td>NASDAQ OMX</td><td></td><td colspan="2"></td><td>✓</td><td>✓</td></tr>
<tr><td rowspan="2">France and Germany</td><td>EPEX</td><td>EPEX Spot</td><td>✓[3]</td><td>✓</td><td>✓</td><td></td><td></td></tr>
<tr><td>EEX</td><td>EEX Power Derivatives</td><td></td><td></td><td></td><td colspan="2">✓</td></tr>
<tr><td rowspan="4">Netherland and Belgium</td><td rowspan="4">APX-ENDEX</td><td>APX Power NL</td><td>✓</td><td colspan="2">✓</td><td></td><td></td></tr>
<tr><td>ENDEX Power NL</td><td></td><td></td><td></td><td>✓</td><td>✓</td></tr>
<tr><td>Belpex</td><td>✓</td><td colspan="2">✓</td><td></td><td></td></tr>
<tr><td>ENDEX Power BE</td><td></td><td></td><td></td><td>✓</td><td>✓</td></tr>
<tr><td rowspan="2">Spain and Portugal</td><td rowspan="2">MIBEL</td><td>OMIE Spain</td><td>✓</td><td colspan="2">✓</td><td></td><td></td></tr>
<tr><td>OMIP Portugal</td><td></td><td></td><td></td><td colspan="2">✓</td></tr>
</table>

[2] Estonia is also included in the electricity market of Nordic Countries

[3] Also covers Austria and Switzerland

Country	Power Exchange	Markets	Physical Trading			Financial Trading	
			Day-ahead	Intra Day Continuous		Futures	
			Auction	Spot	Prompt	Base	Peak
Italy	GME	MPE[4]	✓	✓			
	IDEM	IDEX				✓	

2.3.2 Energy Trading Mechanisms

Forward market handles agreements of bilateral trades many months or years in advance of actual physical delivery time. These bilateral agreements can be reached by direct-search for suitable partners, through electronic bulletin-boards or by facilitation of a broker as discussed earlier. In addition, futures market is a financial counterpart of forward market that allows trading of standardized forward contracts, for all hours of a day or distinctly divided into base or peak loads (see Table 2.2), without any obligation of physical delivery. Interestingly, participants in futures markets can also include speculators who do not actually consume or produce electricity but trade in hope of making profits. Presence of speculators may contribute to greater market liquidity because they increase the number of participants who are likely to buy or sell electricity. Trading in forward market is based on long term load forecast that may not match with actual load requirements and unpredictable faults may cause a generating unit to shut down or curtail its output. Furthermore, participants may not be able to secure bilateral contracts to fulfil their complete trading requirements.

[4] MPE is additionally responsible for the ancillary services market (MSD)

Therefore, forward and future markets alone are not sufficient to maintain reliability of power system and organized markets are also necessary. On the other hand day-ahead market and intraday market fall in this category of organized markets. Day-ahead market conducts a double blind auction for energy on a day-ahead basis by collecting bids from market participants until a set time and then running market clearing algorithm. Although Day-ahead market uses a short term load forecast for next day (more accurate than long term load forecast for forward market), actual load conditions can vary considerably. This is where intraday market plays its role and facilitates continuous trading to bridge any gaps between already agreed arrangements (through forward market or day-ahead market) and varying energy requirements during the actual delivery day.

Continuous trading in intraday market differs from auction in day-ahead market because it requires bids to be executed immediately or as soon as appropriate price becomes available. Sometimes continuous trading is distinctly divided into two types called spot and prompt (see Table 2.2) that are defined in Section 2.3.1. Finally balancing ensures that energy production balances transmission losses and actual consumption for every moment of real time operation.

Flow-based Market Coupling is planned for day-ahead electricity market in Europe as a whole. In Flow-based Market Coupling, a number of power exchanges collect bids and offers from their respected areas and then submit these to a central company, like Electricity Market Coupling Company, that runs a market clearing algorithm. Within the overall electricity market coupling scenario, Nord Pool implements market splitting in its region which consists of multiple price zones. This market splitting is similar to LMP because transmission network is used without any simplification while calculating Security Constrained Optimal Power Flow (SCOPF) The SCOPF guarantees minimum generation cost, power balance at each node, line flows within transmission capacities as well as system security even if a transmission line fails. However, there is a difference in market splitting and LMP because market splitting ensures equal price at all nodes in a zone [27] whereas LMP allows different prices at all nodes of a power system.

2.3.3 Transmission Arrangements

Flow-based Market Coupling is considered a suitable way to deal with transmission arrangements because it can be implemented without undertaking a major restructuring of current power exchanges. Although, Flow-based Market Coupling uses a simplified model of transmission grid as compared to LMP and MS, according to [4] Flow-based Market Coupling should be 'equivalent' to Security Constrained Economic Dispatch. In Flow-based Market Coupling, a central company runs a MC algorithm that ignores any intra-zonal transmission congestion and all nodes within a zone are aggregated into a single node. Even the inter-zonal transmission lines between two neighbouring zones are aggregated into a single interconnector for each border. Meanwhile, all TSOs cooperate to calculate available transmission capacities and provide it to the market coupling company. The company runs market coupling algorithm is run to achieve an overall optimal solution which considers inter-zonal loop flows and transmission capacity constraints [4].

There is a major problem because Flow-based Market Coupling has not been implemented in practice yet so there is no uniform formulation for it such as, for example, SCOPF. There are many political conceptual market coupling proposals but an agreeable implementation model is yet to emerge. After admitting that applying network constraints to auction problem in power exchanges is not straightforward, design of a market coupling algorithm for Europe has been presented in [28]. Detailed mathematical formulation is provided but it is not quite clear whether it is flow based or not. However, mathematical models of congestion management under Flow-based Market Coupling are presented in [29] and [30].

Officially, details of actual market coupling are still emerging and will need to be worked out and then implemented. This has been made clear in a report [31] by EU's Directorate General of Internal Policies on "EU Energy Markets in Gas and Electricity - State of Play of Implementation and Transposition". The report admits that, "In short, there are advances in price coupling and building spot markets in many regions, but while these developments take place, a clear vision of how the regional markets should be built is not yet in place." Further along the report it is stated that, “Whether the existing power exchanges consolidate into regional or EU level operators and/or a reference model for further integration emerges through this development is unclear.” Although, brief Framework Guidelines on Capacity Allocation and Congestion Management [32] are now available, detailed Network Codes are still under preparation. It is expected that exact implementation details of market coupling will emerge when the Network Codes become readily available.

Power exchanges handle day-ahead and intraday trading by implicit allocation of transmission capacity made available by TSOs. On the other hand, TSOs are responsible for running a balancing market or a balancing mechanism in their control zone in real time. In addition, TSOs coordinate at each border to explicitly allocate transmission capacity of interconnector for inter-zonal forward bilateral contracts that are directly agreed between market participants.

A simulation of market coupling for European day-ahead market can be found in [33] and it concludes that MC gives better results than a single power exchange for whole Europe operating on the principle of market splitting. However, [34] casts serious doubts on the adequacy of the intraday market design in Electricity Market Target Model, favouring a real time market like PJM. Wind power capacity in Europe is expected to reach a very high level by the end of this decade, but its intermittent nature presents considerable challenges to balancing power system in real time. It is felt that well-functioning balancing markets are essential for large scale integration of wind power in European power system [35].

2.4 Comparison of Market Designs of the USA and the EU

This chapter seeks to establish *criteria characteristics* and extent of implementation differences in wholesale electricity market mechanisms of the two continents. Discussion in sections 2.2 and 2.3 shows that deregulated wholesale electricity markets designs of the USA and the EU have a number of differences. It is critical to examine the extent of implementation differences in wholesale electricity markets’ mechanisms in North America and Europe. This is examined, in Section 2.4.2 below, to determine whether simulation models of markets in one continent, e.g. North America, can be used for simulation of markets in the other continent, i.e. Europe. Despite different market designs, there are a number of common characteristics in the two market environments. In order to determine suitability of existing simulation models and techniques for wholesale electricity markets, it is imperative to know criteria characteristics of real world market operations. The criteria characteristics of the market environments are discussed in Section 2.4.1.

2.4.1 Criteria Characteristics of Market Environments

The *criteria characteristics* of the market environments in deregulated wholesale electricity markets of North America and Europe are summarized as follows. This summary of the *criteria characteristics* only examines day-ahead markets and annual decision making processes for bilateral transactions and FTRs. Day-ahead market is *dynamic* because of two reasons. First, each GenCo and LSE can modify its hourly offers and bids for energy auction on daily basis. Consequently hourly LMPs of the day-ahead energy market can vary on daily basis. This shows how *dynamic* individual decisions by autonomous participants can have unpredictable *dynamic* market-wide consequences.

At the time of annual decision making, GenCos and LSEs are fully aware of prices in the past year but do not know for sure what prices will occur throughout the coming year. Annual decision making includes deciding energy prices for annual bilateral transactions and bidding prices for annual FTRs auction. However, GenCos and LSEs can undertake statistical analysis of prices in the past year to determine expectation, variance and covariance of prices for the next year. Furthermore, GenCos and LSEs can use the annual results of prices' statistical analysis while deciding energy prices for annual bilateral transactions for the next year. GenCos and LSEs can also use the annual results of prices' statistical analysis while deciding bidding prices for annual auction of FTRs for the next year. The annual results of prices' statistical analysis can vary from year to year due to *dynamic* nature of day-ahead market. Consequently, annual decision making by GenCos and LSEs, for deciding prices of bilateral transactions and bidding prices for annual Financial Transmission Rights auction, takes place under *dynamic* market conditions.

A real world power system has *transmission constraints* because its transmission network has physical limitations to maximum power flows through transmission lines. Therefore, a transmission operator has to manage transmission network and all market operations are performed in a market environment that has *transmission constraints*.

Day-ahead market for energy is arranged by an independent system operator and a market operator in the USA and the EU respectively. Annual market for FTRs is arranged by an independent system operator and a transmission operator in the USA and the EU respectively. Therefore, both day-ahead market for energy and annual market for FTRs are *organized* markets. Decision making for bilateral transactions can involve two phases; *match making* and *bilateral negotiations*. Short duration bilateral transactions are usually *organized* bilateral transactions because *match making* for such transactions takes place through broker or via online bulletin-board. However, medium and long duration bilateral transactions are normally *direct-search* bilateral transactions because participants conduct private search for *match making* with suitable partners. In general, *match making* for bilateral transactions is not a random process but rather depends on some *systematic* procedures, such as portfolio optimization.

In multi-round *bilateral negotiations* for price and amount of energy, GenCos and LSEs can have *mixed* tasks that are both *competitive* and *cooperative*. A GenCo or an LSE has a *cooperative* task when it concedes from its previous-round offer or demand in an attempt to secure a bilateral transaction. The *cooperative* task stems from the fact that if a GenCo and an LSE can agree on a bilateral transaction then both participants can avoid risk of uncertain prices in day-ahead market. Besides the *cooperative* task, a GenCo or an LSE can also have a *competitive* task. A GenCo has a *competitive* task when it concedes in a restrained way in an attempt to secure a bilateral transaction at as high a price as possible. As a mirror image, an LSE has a *competitive* task when it concedes in a restrained way in an attempt to secure a bilateral transaction at as low a price as possible.

Participants in both annual Financial Transmission Rights auction and day-ahead market's energy auction mostly have *competitive* tasks because all participants compete for a market share. Both of these auctions are prone to collusion in participants and exercise of market power by one or more participants. However, collusion in participants and market power aspects are not considered in this research.

Market participants have *incomplete information* about each other during all market operations. For example, participants are unaware of private risk preferences or profits of other participants. Furthermore, market participants can observe overall market outcomes but do not know details of underlying market operations. For instance, market operator only announces clearing prices and amounts in auctions but does not publicly release data submitted in participants' bids. As a matter of fact, even the market operator does not know actual cost of a GenCo or actual benefit to an LSE but only knows data submitted in their bids. Therefore, each market participant and the market operator have *incomplete information* about others.

2.4.2 Detailed Comparison of Both Market Designs

A comparison of general aspects of prevailing wholesale electricity market designs in Europe and North America is presented in Table 2.3. Although there are considerable differences among markets within each continent, Wholesale Power Market Platform is considered to be the prevailing design for North America and Electricity Market Target Model to be the one for Europe in this chapter. Interestingly, Nord Pool has some peculiar features but also shares some characteristics of both designs so it is included in the comparison as a special case. Both the prevailing USA markets and most European markets have bulk bilateral forward trades followed by lesser day-ahead trading. Until a few years ago, it was also true for Nord Pool but it is no longer the case now.

Table 2.3 General Comparison of Wholesale Electricity Market Designs of Europe and North America

	Prevailing Design in North America	**Current Design in Nordic Countries**	**Emerging Design for whole Europe**
Model	Wholesale Power Market Platform	Nord Pool	Electricity Market Target Model
Interaction of Transmission and Market Operators	ISO and RTO are combined into a single entity	Power Exchange and TSOs are essentially independent organizations	Power Exchanges and TSOs are essentially independent organizations
Market Operator	Single Power Pool	Single Power Exchange	Multiple Power Exchanges
Transmission Operator	Single Transmission Operator	National Transmission Operators	National Transmission Operators
Market Participation	Mandatory or incentive-based	Voluntary or open	Voluntary or open
Ownership	Public	Public	Private Power Exchanges, Public TSOs
Volume of Day-ahead Auction Market & Forward Bilateral Trade	More Bilateral Trade and Less Auction Market	More Auction Market and Less Bilateral Trade	More Bilateral Trade and Less Auction Market

Energy trading mechanisms and transmission arrangements in markets of the two continents are compared in Table 2.4 and Table 2.5 respectively. In preparation of these tables, research presented in [4] and [28] has been found particularly interesting and useful. Energy trading mechanisms in the two continents are compared in Table 2.4. First three rows of Table 2.4 cover generator bidding and generation scheduling. In this regard, Nord Pool is same as other markets in the EU which are all distinctly different from the USA markets. In the USA markets, absence of blocks means generators express their no-load and start-up costs and consequently generators are incentive compatible. In the European markets, generators are unable to directly express their fixed costs but blocks allow expression of multi-period cost structures [28]. So both systems facilitate some means of recovering start-up and no-load costs of generation, one way or the other.

Last four rows of Table 2.4 cover bids processing and its results in terms of nature of pricing. It is suggested in [27] that the objective function of overall cost minimization in the USA markets is synonymous, despite being mathematically different, to social welfare or surplus maximization in the European markets. Although, optimization procedures and underlying solution methodologies are not the same in the three cases discussed here, it appears that they have some similarities. However, despite the apparent similarities, there are striking differences among the three cases that become increasingly crucial, when actually implementing any particular type of auction for simulation purposes.

Table 2.4 Comparison of Operations of Generators in Wholesale Electricity Markets of Europe and America

	Prevailing Design in North America	**Current Design in Nordic Countries**	**Emerging Design for whole Europe**
Generator Hourly Bids in Day-ahead Market	Cost-based Multi-part bids containing Fuel cost, No load cost and Start-up cost	Price-based Single-Part bids containing Price and Energy Volume	Price-based Single-Part bids containing Price and Energy Volume

	Prevailing Design in North America	**Current Design in Nordic Countries**	**Emerging Design for whole Europe**
Generator Data with Bids for Day-ahead Market	Detailed generator data including operating and ramp limits and minimum up and down times	Operating limits are implicit in the bid. No ramp limits or minimum up and down times are provided.	Operating limits are implicit in the bid. No ramp limits or minimum up and down times are provided.
Generator Block bids	No block bids	Multi-hour block bids	Multi-hour block bids
Generator Scheduling	Partially Self-Scheduling with centralized Unit Commitment	Fully Self-Scheduling without centralized Unit Commitment	Fully Self-Scheduling without centralized Unit Commitment
Objective Function	Overall Cost Minimization	Social Welfare Maximization	Social Welfare Maximization
Optimization Procedure	SCOPF	The optimization method is similar to SCOPF	Optimization by Flow Based Market Coupling
Underlying Programming Concept	Mixed Integer Programming	Not Known	Mixed Integer Quadratic Programming or Mixed Integer Linear Programming variants of Mixed Integer Programming

	Prevailing Design in North America	**Current Design in Nordic Countries**	**Emerging Design for whole Europe**
Zonal/Nodal Pricing	Nodal Pricing called Locational Marginal Price (LMP)	Zonal Pricing by aggregating nodes into Zones	Zonal Pricing called Market Clearing Price
Linear/Non-Linear Pricing	Pay-as-Bid/Nonlinear consisting of an hourly reference price and an extra payment	Uniform/Linear, only hourly price	Uniform/Linear, only hourly price

A comparison of transmission operation in the two continents can be seen in Table 2.5. Transmission capacity allocation method for forward bilateral trades is not the same in all three markets but it will become effectively the same if only obligation FTRs are adopted for all interconnectors in Electricity Market Target Model. It will be so because Contracts for Difference in Nord Pool are financial instruments for hedging against congestion risk like FTR that are commonly used in the USA markets. However, unlike FTR that are issued by ISOs, Contracts for Difference are futures traded on NASDAQ OMX to cover congestion charge for inter-zonal bilateral trades due to price differential between neighbouring zones. In fact, use of FTRs as obligations in Electricity Market Target Model is put forward as the most important recommendation by a comprehensive recent report [4]. It is clear that if FTRs are introduced then it will be an important step towards reducing differences between electricity markets in Europe and North America. Furthermore, it is proposed that either type of transmission rights must be allocated through coordinated explicit auctions by TSOs of neighbouring zones. Intra-zonal physical bilateral trades take place subject to applicable transmission tariffs but without participating in implicit auction by power exchange. On the other hand, inter-zonal transmission capacity allocation method for day-ahead market is implicit auctioning by market operator in all three cases discussed in Table 2.5. In Electricity Market Target Model, implicit auctioning for inter-zonal transmission capacity is proposed to be carried out via a single price coupling algorithm [32]. In the European day-ahead markets, congestion rents are charged as per applicable tariffs for intra-zonal transmission capacity. In Nord Pool, like the USA, no simplifications to the transmission network are made when checking for flow feasibility. On the other hand, in Electricity Market Target Model, whole zone is modelled as a single node and all inter-zonal transmission lines for two adjacent zones are aggregated into a single interconnector for modelling [4]. It is sensible to model many real interconnectors by a single aggregated interconnector because a single control centre in each zone manages total available transmission capacity between two neighbouring zones. It can also be necessary to aggregate interconnectors because of commercially sensitive nature of data about individual interconnectors.

Table 2.5 Comparison of Operation of Transmission in Wholesale Electricity Markets of Europe and America

	Prevailing Design in North America	**Current Design in Nordic Countries**	**Emerging Design for whole Europe**
Transmission Capacity Allocation Method for Forward Bilateral Trades	Financial Transmission Rights (FTR) are explicitly auctioned in a separate FTR market by RTO.	Special Contracts for Difference are used for inter-zonal bilateral trades.	Physical Transmission Rights as Options. OR Financial Transmission Rights (FTR) as options or obligations.

	Prevailing Design in North America	**Current Design in Nordic Countries**	**Emerging Design for whole Europe**
Transmission Capacity Calculation Method for Day-ahead Market	Locational Marginal Pricing	Market Splitting	Flow Based Market Coupling
Transmission Capacity Allocation Method for Day-ahead Market	Implicit Auction of all Transmission Capacity along with Energy traded through pool	Implicit Auction of Inter-zonal Capacity. Congestion rent for Intra-zonal transmission	Implicit Auction of Inter-zonal Capacity. Congestion rent for Intra-zonal transmission
Transmission Network Constraints	Fully taken into account and reflected in location based prices which can differ for each node	Both inter-zonal and intra-zonal constraints are fully considered.	Intra-zonal constraints are ignored and Inter-zonal constraints are simplified.

2.5 Conclusions

In general, wholesale electricity markets have *transmission constraints* and *dynamic* environments. Both day-ahead market for energy and annual market for FTRs are *organized* markets. Decision making for bilateral transactions can involve two phases; *match making* and *bilateral negotiations*. Short duration bilateral transactions are usually *organized* bilateral transactions but medium and long duration bilateral transactions are normally *direct-search* bilateral transactions. The *match making* phase for deciding suitable trading partners is not a random process but rather depends on some kind of *systematic* procedures. In multi-round *bilateral negotiations* phase for deciding price and amount of energy, GenCos and LSEs can have *mixed* tasks that are both *competitive* and *cooperative*. By comparison, participants in both annual Financial Transmission Rights auction and day-ahead market's energy auction mostly have *competitive* tasks. Each market participant and the market operator interact among themselves with *incomplete information* about others.

Despite initial reservations, all electricity markets in the USA with a day-ahead auction have already implemented (MISO, PJM) or are set to adopt some version of Wholesale Power Market Platform (SPP, ERCOT) in near future. In contrast, decentralized forward bilateral transaction along with centralized real time balancing is used in the rest of the USA. In EU, over the last few years, although electricity markets have gradually achieved market coupling over greater areas and with increasing sophistication, exact implementation details of Electricity Market Target Model are yet to emerge.

A general comparison of electricity markets in the two continents reveals that they are overwhelmingly different. This implies that in general aspects Nord Pool is similar to the Electricity Market Target Model. However, Nord Pool has higher volume of bilateral trades as compared to auction market which is contrary to the general trend in Electricity Market Target Model. In addition, unlike private power exchanges in the rest of Europe, complete power market is in public sector in Nord Pool. While comparing operations of generators and results of bids processing in the two continents, it becomes clear that markets in the two continents are completely different. However, in terms of transmission management the Nord Pool mostly resembles Wholesale Power Market Platform, with the exception that for day-ahead market it uses implicit auction of inter-zonal capacity and congestion rent for intra-zonal transmission in the same way as the Electricity Market Target Model. The process of bids handling has apparent similarities in all three markets as far as objective function is concerned but mathematical details of each approach are different from each other.

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3 Review of Simulation Models and Techniques for Electricity Markets

3.1 Introduction

Emergence of competitive electricity markets and subsequent adjustments in market designs have encouraged market modelling for analysis and research. Overall models for electricity markets, composed of explicit modelling for both generation and load sides, can be broadly divided into game-theoretic equilibrium models and agent-based simulation models. This chapter discusses some game-theoretic equilibrium models followed by a review of agent-based simulation models for electricity markets. In addition, it is highlighted that learning and optimization techniques for specific operational problems of individual market participants can contribute to overall simulation of an electricity market.

Common characteristics of wholesale electricity market environments, discussed in the last chapter, are summarized as follows. In general, wholesale electricity markets have *transmission constraints* and *dynamic* environments. Both day-ahead market for energy and annual market for FTRs are *organized* markets. Decision making for bilateral transactions can involve two phases; *match making* and *bilateral negotiations*. Short-duration bilateral transactions are usually *organized* bilateral transactions but medium and long duration bilateral transactions are normally *direct-search* bilateral transactions. Long-duration bilateral transactions are useful to secure investments for new generation resources. Further discussion of long-duration bilateral transactions is beyond the scope of this chapter.

This chapter restricts discussion of bilateral transactions to *organized* short-duration and *direct-search* medium-duration bilateral transactions because these transactions hedge against uncertainty of day-ahead market prices and this thesis aims to achieve combined simulation of bilateral transactions and day-ahead market. These two types of bilateral transactions hedge risks of price fluctuations in day-ahead market. The *match making* phase for deciding suitable trading partners is not a random process but rather depends on some kind of *systematic* procedures. In multi-round *bilateral negotiations* phase for deciding price and quantity of energy, GenCos and LSEs can have *mixed* tasks that are both *competitive* and *cooperative*. By comparison, participants in both annual Financial Transmission Rights auction and day-ahead market's energy auction mostly have *competitive* tasks. Each market participant and the market operator interact among themselves with *incomplete information* about others. Suitability of simulation models/techniques reported in literature will be examined and discussed on the basis of criteria characteristics (written in italics) in this paragraph.

Prior to further discussion on agent based modelling, it is vital to define the meaning of agent and environment in context of wholesale electricity market simulations. A market participant can be represented by a software agent in simulation. Simulated environment of an agent has two distinct parts; other agents and overall market. A simulation may model behaviours of agents in the environment as *stationary*, *dynamic* or *adaptive* strategies. It is critical to differentiate among *stationary*, *dynamic* and *adaptive* strategies for the purposes of this thesis. An agent has a *stationary* strategy if it shows deterministic behaviour that does not change after repeated interactions with the environment. An agent has a *dynamic* strategy if it modifies its behaviour <u>after</u> experiencing <u>overall dynamics of its environment</u>. An agent has an *adaptive* strategy if it adjusts its behaviour in reaction to an opponent's responses <u>during</u> interactions with <u>that individual opponent</u>.

Moreover, a simulation may consider conditions of overall market environment, for instance prices of *organized* market, to be *stationary* or *dynamic*. Some simulations assume that each market participant and/or the market operator interact among themselves with *complete information* about others. In addition, some simulations ignore *transmission constraints* on bilateral transactions.

In a simulation, market participants may have purely *cooperative* or purely *competitive* or both *cooperative* as well as *competitive* tasks. Tasks that have *cooperative* as well as *competitive* elements are called *mixed* tasks. Game theoretic concepts are necessary to understand and describe behaviours of participants in simulations of electricity markets. Since game theory is useful for mathematical modelling of participants' strategic behaviours, some necessary game theoretic concepts are presented here.

In team efforts, participants are *cooperative* with each other because they have a common goal. Therefore team games are known as *common-payoff* games. By comparison, participants of a two-player game will be very *competitive* if there is no draw and only the winner gains $1000 and the loser loses that $1000. If gain of one participant is exactly the same as the loss of the other participant then it is called a *zero-sum* game.

In multi-round *bilateral negotiations* phase for deciding price and quantity of energy, GenCos and LSEs can use *mixed* behaviours. If a GenCo and an LSE can secure a bilateral transaction then it is a win-win scenario because both parties gain some utility and reduce their risks. Such a win-win scenario is called a *general-sum* game because utility gains of GenCo and LSE add up to some general non-zero number.

3.2 Approaches for Overall Modelling of Bilateral Transactions in Electricity Markets

It is crucial to model both generation and load to gain better insight into bilateral transactions. Overall models for electricity markets, composed of explicit modelling for both generation and load, can be broadly categorized as game-theoretic equilibrium models and agent-based simulation models. This section discusses three game-theoretic equilibrium models followed by a review of agent-based simulation models for electricity markets, with emphasis on modelling of bilateral trades.

3.2.1 Game Theoretic Equilibrium Models

Game-theoretic equilibrium models lead to optimal solutions but these are based on an assumption that each participant has *complete information* about strategies of other participants [1]. Stakelberg equilibrium solution has been used for *match making* in [2] and [3]. Nash Equilibrium and Nash Bargaining are two game-theoretic models that have been used in simulation of *bilateral negotiations* for bilateral electricity trades.

An application of Stakelberg equilibrium solution for *match making* in [2] and [3] assumes that all buyers are *cooperative* with each other and represented by a single decision maker. The same is assumed for all sellers. However, the two representative decision makers are assumed to be mutually *competitive*. It further assumes that both decision makers have *complete information* about desires and objectives of all market participants.

Limitations of Nash Bargaining are that it can only involve two players and it is a fully *cooperative* game that ignores competition. For bilateral transaction between two players at the same node (and therefore with no need to consider *transmission constraints*) it was assumed in [4] that each player has *complete information* of other's private utility function.

Nash Equilibrium can involve two or more players but it assumes *complete information* about equilibrium strategies of other players. Furthermore, it is a fully *competitive* game that has been applied to bilateral negotiation for electricity trades in a system consisting of three generators and two loads [5]. However, work in [5] has been criticized in [6] by proving that the suggested Nash equilibria are inconsistent with the Nash Equilibrium. In consequence, Nash Equilibrium has not yet been proved suitable for representation of bilateral electricity trades.

Therefore, the weakness of the game-theoretic models for simulation of bilateral transactions among multiple participants with *incomplete information* is that they assume complete information. In contrast, agent-based models allow agents to keep their information private and therefore better suit bilateral interaction of multiple participants with *incomplete information*. Advantages of agent-based models are discussed in the following subsection.

3.2.2 Agent-based Simulation Models

Merits of agent based simulation vis-á-vis traditional methods are discussed in [7], [8] and [9]. These merits include private goal-directed learning and self-determination by market participants [9]. Another merit of this approach is ease of modelling complex behaviour of a variety of system participants in large scale systems [8]. Bilateral transactions are an important aspect of the electricity markets that can perhaps best be represented in agent based simulation models [7] because of following reasons. Agent-based models facilitate analysis of distributed decision making such as *match making* for *direct-search* bilateral transactions and *bilateral negotiations*. Furthermore, participants have *incomplete information* about others because each participant is modelled as a separate agent with private information. As a result, agent-based simulation models can cater *competitive, cooperative* or *mixed,* behaviours among multiple participants.

Comprehensive literature reviews of a large number of agent-based simulation models of electricity markets are available in [7], [8], [10], [11] and [12]. For instance, a comparison table in [12] lists fifty papers that report agent-based simulation models for wholesale electricity markets. However, research presented in this thesis focuses on models that are suitable for combined simulation of day-ahead auction and bilateral transactions. Consequently, only following three categories of agent-based simulation models are discussed here: (i) agent-based simulation models which are capable of the combined simulation; (ii) open-source agent-based simulation models, with a potential of extension for the combined simulation and (iii) agent-based simulation model developed by this research.

Table 3.1, adapted from a table in [12], presents a comparison of only these three categories of agent based simulation models. In addition to the models that were presented in the table in [12], Table 3.1 also includes two other, well known, models EMCAS [13] and NEMSIM [14]. Furthermore, Table 3.1 includes Provenzano's model [15] as well as updates in capability of MASCEM [16].

As mentioned earlier, bilateral transactions can be *direct-search* or *organized*. Decision making for bilateral transactions consists of two phases called *match* *making* and *bilateral negotiations*. The first four models in Table 3.1, PowerACE, Marketecture, Provenzano and Bower&Bunn are non-commercial and not useful for medium-duration *direct-search* bilateral transactions because they model short-duration *organised* bilateral transactions, as discussed in the next two paragraphs.

In Marketecture model presented in [17], *match making* of buyers and sellers is determined randomly or by the software user. Then, *bilateral negotiation* is simulated in a single software module that has *complete information* of generators cost functions and consumers demand functions. On the other hand, PowerACE is reported to use a bulletin-board facilitator in [18] for *match making* of *organised* bilateral transactions. Buyers and sellers continuously post their bids to the bulletin-board and *match making* is unpredictable because it takes place whenever a buyer's bid matches a seller's bid. PowerACE achieves *match making* for *organised* bilateral transactions by a *systematic* approach. Furthermore, since PowerACE achieves exact *match making* by a bulletin-board, there is no need for *bilateral negotiations*. As suggested in [18], "the realistic representation of bilateral transaction and matchmaking in forward trading is still subject to further research". The term "realistic" can be interpreted to mean *match making* for *direct-search* bilateral transactions by a *systematic* approach. In addition, it can mean *bilateral negotiations* between participants with *incomplete information* about each other. In Bower&Bunn [19], bids for short-duration bilateral transactions during next day and day-ahead auction are collectively cleared by market operator. Therefore, market operator has *complete information* of bid prices and quantities of all market participants.

In Provenzano [15], each agent constructs its own weighted tree of desired attributes like price and energy quality. Then, assuming *complete information* of all agents' attributes, an algorithm determines a similarity measure for every agent with its opponent agents. After *match making*, every agent lists its opponent agents in decreasing order of similarity. Each agent solely relies on *time-dependent strategy* and starts negotiation with the first opponent in the list. If negotiation fails with the first opponent in the list then second opponent is chosen and so on. However, a drawback of this negotiation approach appears if buying and selling agents do not have each other at the same level in their lists, assuming same negotiation time preferences for both agents. This means that if the level is not the same then when a buyer is interested in a particular seller, the seller may be interested in another buyer. At a later time, that seller may become interested in the earlier buyer but since the buyer has already exhausted its option of engaging with the particular seller, the buyer is no more interested in the seller. A sophisticated negotiation approach can solve this problem if it facilitates simultaneous negotiations with a number of opponent agents for different power quantities and prices. However, in that case a negotiating agent will have to decide how much of power quantity to trade with which particular agent and at what price.

The subsequent three models in Table 3.1 are EMCAS, NEMSIM and MASCEM which have been marketed as commercial software. Overviews of these three models are presented in [13], [14] and [16] respectively. These overviews indicate that bilateral transactions are included in these models. For instance, use of private risk aversion factors, price expectations and price volatility is mentioned for EMCAS [13]. Similarly, feedback loops between day-ahead auction and bilateral transactions market representing hedging decisions are mentioned in [14] for NEMSIM. Agents in MASCEM use time-dependent and behaviour-dependent negotiation strategies [16]. Full mathematical models of *match making* or *bilateral negotiations* are not publicly available to research community for commercial and proprietary software like EMCAS, NEMSIM and MASCEM.

It is important to note that compared to above-discussed agent based simulation models, AMES lacks modelling of bilateral transactions and is the only open source software. Advantages and some issues of open source software development for electricity markets research are discussed in [20]. There are some general design and development issues with all open source software. Nevertheless, open source software provides free access and detailed understanding of implemented model as compared to proprietary software. This makes it possible to modify and extend the open source software for specific research and training needs. AMES already models a day-ahead market for auction of energy. Because of that, this research has developed new software that builds on AMES by incorporating models of bilateral transactions and *financial transmission instruments*. The new software is named

“Financial transmission instruments, energy Auction and Bilateral transaction Simulator for wholesale electricity markets”, abbreviated as FABS. AMES and FABS are described in the following subsections respectively.

Table 3.1 Comparison of New and Previous Agent-based Simulation Software for Wholesale Electricity Markets

Model	DP	UP	LMP	ARR	FTR	TC	BTM	DAM	RTM	COS	OSS
PowerACE [18]		✓					✓	✓	✓		
Marketecture [17]						✓	✓	✓			
Bower&Bunn [19]	✓	✓					✓	✓			
Provenzano [15]		✓					✓	✓			
EMCAS [13]	✓		✓			✓	✓	✓	✓	✓	
NEMSIM [14]			✓			✓	✓	✓	✓	✓	
MASCEM [16]		✓				✓	✓	✓	✓	✓	
AMES			✓			✓		✓	✓		✓
FABS			✓	✓	✓	✓	✓	✓	✓		✓

DP = Discriminatory Price, UP = Uniform Price, LMP = Locational Marginal Price, TC = Transmission Constraints, ARR= Auction Revenue Rights, FTR = Financial Transmission Rights, BTM = Bilateral Transactions Market, DAM = Day-ahead Market, RTM = Real-Time Market, COS = Commercial Software, OSS = Open Source Software

3.2.2.1 AMES Software

In 2003, a Wholesale Power Market Platform (WPMP) was proposed for USA-wide adaption by Federal Energy Regulatory Commission (FERC). AMES was developed for systematic experimental testing of the WPMP design proposed by the FERC [21]. In [22], AMES is described as a computational laboratory for research, teaching and training. A number of ISOs, including Midcontinent ISO (MISO) and ISO New-England (ISONE), have adapted some version of the WPMP design. Architecture of

AMES is based on business practice manuals for MISO/ISONE [23]. Main features of AMES are described in [22] and outlined as follows.

AMES models a transmission network managed by an ISO. A number of energy traders are distributed across the nodes of transmission network. The energy traders include GenCos that are bulk-energy sellers and LSEs that are bulk-energy buyers. The objective of ISO is maximization of total net benefits subject to generation and transmission constraints. Therefore, ISO conducts a day-ahead auction for energy settled by LMP.

The objective of each LSE is to secure energy for loads that it serves and thus, each LSE submits a demand bid to ISO for day-ahead auction. The model assumes that LSEs do not have learning capabilities and submit user-defined hourly demand bids. The objective of each GenCo is to secure maximum possible profits every day. Each GenCo submits an hourly supply offer to ISO for day-ahead auction. In contrast to LSEs, each GenCo has learning capability to modify its supply offers in order to meet its objective.

ISO receives demand bids for LSEs and supply offers from GenCos, and then clears day-ahead auction by hourly DC Optimal Power Flow described in [24]. ISO publicly declares auction results including GenCos' energy supply commitments and LMPs. After announcement of daily market clearing results by ISO, each GenCo reviews its performance and uses reinforcement learning, described in [25], to improve its supply offers for the next day.

AMES was developed as agent-based and open-source software to facilitate future extensions in its capabilities. In [26], AMES architecture is graphically illustrated and it is indicated that bilateral and FTR markets need to be incorporated in future software.

3.2.2.2 FABS Software

AMES models a day-ahead energy auction but no bilateral transactions or *financial transmission instruments*. Building on AMES, this research has developed FABS that incorporates models of bilateral transactions and *financial transmission* *instruments*. As pointed out in previous chapter, despite some common characteristics, market designs of the EU and the USA are overwhelmingly different. Since day-ahead market in AMES follows model of the USA markets, FABS also models operations in the wholesale electricity markets of the USA. Like AMES, FABS is also based on information in business practice manuals and training materials for MISO/ISONE. However, in the same way as AMES, FABS is not intended to model or test market design of any particular ISO, including MISO and ISONE.

The main contribution of FABS is to model bilateral transactions and *financial transmission instruments* in wholesale electricity markets of USA in general. In addition, FABS has integrated the models of bilateral transactions and *financial transmission instruments* with day-ahead auction model that existed in AMES. Therefore, FABS is capable of combined simulation of *financial transmission instruments*, bilateral transactions and day-ahead auction for energy. Complete model of FABS is presented in Chapter 4.

Features of FABS are also compared with previously existing agent based simulation software in Table 3.1. The table shows that only FABS includes *financial transmission instruments* (Financial Transmission Rights and Auction Revenue Rights).

The following three sections include reviews of simulation techniques for *match making*, *bilateral negotiations* and *financial transmission instruments* in wholesale electricity markets of the USA. These literature reviews focus on *match making* and *bilateral negotiations* because this thesis aims to model decentralized medium-duration bilateral transactions. In addition, the review includes *financial transmission instruments* because this thesis intends to model these along with bilateral transactions.

3.3 Simulation Techniques for Match Making

Before exploring simulation techniques for *match making*, it is essential to note the following criteria characteristics (written in italics) for determining suitability of a technique. As mentioned earlier, short duration bilateral transactions are usually *organized* bilateral transactions but medium-duration bilateral transactions are normally *direct-search* bilateral transactions. The *match making* phase for deciding suitable trading partners is not a random process but rather depends on some kind of *systematic* procedures. Simulation techniques for *match making* of *organized* bilateral transactions and *direct-search* bilateral transactions are now discussed in following two subsections.

3.3.1 Organized Match Making

In [2] and [3], each agent has a tree structure of electricity attributes for bilateral transaction, where each branch of the tree represents a specific attribute of electricity, such as price or quantity. An agent assigns weights, which add up to 1.0, to the branches of its tree. The values of weights represent importance of corresponding attributes for the agent. It is assumed that sellers are *cooperative* with sellers and the same trend prevails among buyers. Because of this, all sellers are represented by a single sellers' decision maker. Similarly, all buyers are represented by a buyers' decision maker which runs an algorithm, from buyers' point of view, to determine a similarity measure for every buyer agent with all seller agents. The sellers' decision maker runs another algorithm, from sellers' point of view, to determine a similarity measure for every seller with all buyer agents. Both algorithms require *complete information* about private weights of electricity attributes for all buyer and seller agents.

Then, the two decision maker agents sequentially use "leader-follower" concept of Stakelberg game solution, to get best matched seller-buyer pairs. Decision makers of buyers and sellers assume role of "leader" and "follower" respectively. Once a seller-buyer pair is matched, both are eliminated from the sequential match making process. In the subsequent iteration of the match making process, the two decision makers match most suitable seller and buyer agents among the remaining agents. The iterations continue until either all buyer or seller agents have been matched. It is argued that use of collective decision makers avoids decision conflict and hence gives optimal results.

In addition to [2] and [3], organized match making is also used in [15] and [27]. Instead of any *systematic* approach, randomly organized match making is modelled in [27] whereas organized match making in [15] has already been explained in sub-section 3.2.2.

Above discussion shows that *match making* in [2], [3], [15] and [27] is not suitable for *direct-search* bilateral transactions because it is based on organized match making. Simulation of *match making* for *direct-search* bilateral transactions is described below.

3.3.2 Match Making by Direct-search

Day-ahead auction involves risks like sudden price spikes and entering into appropriate bilateral transactions can hedge such risks. As a consequence, decision making for entering into bilateral transactions can be improved by proper risk management. In electricity markets, each GenCo and LSE can do its *match making* by determining its own optimal engagements by *portfolio optimization*. A portfolio is a range of engagements held by a GenCo or an LSE. The *portfolio optimization* enables a participant to explore all available engagement options for bilateral transactions throughout the market in a *systematic* way. Participants can use private *portfolio optimization*, instead of some random process, for *match making* in *direct-search* bilateral transactions.

Markowitz [28] is pioneer of modern portfolio theory which is widely used to determine an optimal portfolio as a remedy for uncertainty so that risk can be constrained below a desired level. “The portfolio theory consists of principles underlying analysis and evaluation of rational portfolio choices based on risk-return trade-offs and efficient diversification” [29]. Portfolio optimization methods determine how much energy, if any, should be traded through each of the bilateral transactions, and at what price. These methods also evaluate utility of proposed bilateral transactions.

Portfolio optimization methods of GenCos [29], [30] and LSEs [31] are neither used in agent-based systems nor accommodate *transmission constraints*. However, the portfolio optimization methods could be modified to accommodate *transmission constraints* as well as used in agent-based systems. In that case, portfolio optimization methods will be helpful in *match making* for *direct-search* bilateral transactions.

3.4 Simulation Techniques for Bilateral Negotiation

Different parts and stages of negotiation are presented in [1] and [32] in general terms, and they are helpful in understanding the whole phenomenon of bilateral negotiations. Four negotiation protocols are discussed in [32]: (i) Nash demand; (ii) ultimatum; (iii) alternating offers and (iv) monotonic concession. In case of Nash demand both participants make simultaneous moves. In ultimatum protocol, one participant makes a "take it or leave it" offer to the other participant. Consequently, the other participant has only two options: accept or refuse. Alternating offers is a more flexible protocol that facilitates multi-round *bilateral negotiations*. Participants cannot insist on their position in the last round and they are forced to make concessions in each round or quit. Monotonic concession protocol assumes that both participants make simultaneous moves. For a maximum of two consecutive rounds, each participant is allowed to insist upon its position. However, a participant has to concede in every third round, at the least. In consequence, participants can hold onto their position for at least two consecutive rounds and do not have to make concessions in each and every round.

Before exploring simulation techniques for *bilateral negotiation*, it is important to recall following criteria characteristics (shown in italics) for determining suitability of a technique. As mentioned earlier, GenCos and LSEs can use *mixed* behaviours in multi-round *bilateral negotiations*. If a GenCo and an LSE can secure a bilateral transaction then it is a win-win scenario because both sides gain some utility and reduce their risks. Such a win-win scenario is called a *general-sum* game because utility gains of GenCo and LSE add up to some general non-zero number. Furthermore, prices of *organized* markets are *dynamic* and market participants interact among themselves with *incomplete information* about others. Heuristic and

Learning techniques have been widely used by researchers for simulation of *bilateral negotiation* because of reasons discussed next.

3.4.1 Heuristic Techniques

Heuristic techniques give good (though not optimal) results while using an environment of *incomplete information* about other participants [1]. Heuristic techniques for multi-round *bilateral negotiations* are normally based on a time-dependent strategy, a behaviour-dependent strategy or a resource-dependent strategy [33] and [34]. Two or more strategies can be combined and applied all the time [35], can be assigned relative weights that may vary with time [36] or can be interchanged with the passage of time [37]. According to [37], the range of strategies and policies defined in [33] and [34] are "borrowed from good behavioural practice in human negotiation" so that agents can generate offers and evaluate proposals.

Agent behaviours in multi-round *bilateral negotiations* can be divided into three broad categories; *yielding*, *contending* and *linear*. An agent shows *yielding* behaviour if it makes big concessions in successive rounds. If an agent makes little concessions in successive rounds then it has *contending* behaviour. An agent shows *linear* behaviour if it shows uniform concessions in successive rounds.

If an agent has a deadline to complete multi-round *bilateral negotiations* then it can use *time-dependent strategy*. An agent can use *yielding*, *contending* and *linear* behaviours for *time-dependent strategy*. Three types of *time-dependent strategies* are discussed as follows. In first type, agent uses *yielding* behaviour in the initial rounds and *contending* behaviour in the final rounds. In second type, agent uses *contending* behaviour in the initial rounds and *yielding* behaviour in the final rounds. In third type, agent uses *linear* behaviour in each round of multi-round *bilateral negotiations*.

An agent using *behaviour-dependent strategy* for *bilateral negotiations* imitates its opponent's behaviour as a tit-for-tat. Such an agent uses *linear* or *yielding* behaviour if its opponent shows *linear* or *yielding* behaviour respectively. However, if both agents use *behaviour-dependent strategy* and *contending* behaviour then there is risk that agent positions may not converge quickly. If their positions do not converge by the last round then *bilateral negotiation* will fail. In *bilateral negotiations* for a resource, an agent may use a *resource-dependent strategy* by using *contending* behaviour if the resource is in plenty and *yielding* behaviour if resource is in short supply.

A broker agent simultaneously mediates between all buyer and seller agents for multiple attributes in [38]. The broker ensures that private preferences of agents are hidden from each other. Time constrained and *organised* negotiations are simulated between the seller and buyer agents; preferences of agents can vary over time for multiple attributes. All agents use *time-dependent strategy* for negotiations; at different time steps, agents can choose different degrees of concessions for opponent agents. After *match making* as shown in [3], agents use a combination of *time-dependent strategy* and *behaviour-dependent strategy* for bilateral negotiations in [35].

If negotiating agents only depend on their behaviour-dependent strategies and resort to contending behaviour then there is risk that agent positions may not converge and consequently bilateral negotiation may fail. However, time-dependent strategy is a simple method that can lead to successful bilateral negotiations. In [39] and [40], time-dependent strategy is combined with an assumed measure of bilateral transaction reward that depends on energy prices in a specific price range.

3.4.2 Learning Techniques

Learning techniques allow market participants to discover, over a course of repeated interactions, private intentions of others and accordingly adapt their negotiation strategies for greater financial gains. Four classes of learning techniques are listed in [1] as common choices of negotiators. These broad classes include principle-based or didactic learning; learning by feedback or via information revelation; learning by analogy or analogical learning and observational learning or imitation. A number of learning techniques can also be used for simulating negotiation among intelligent agents [32]. Some of the most promising learning techniques for *bilateral negotiation* are discussed as follows.

3.4.2.1 Reinforcement Learning

In *reinforcement learning*, if an action leads to favourable results then tendency to implement that action should be reinforced, otherwise the tendency should be reduced [41]. An agent using *reinforcement learning* develops association between states and actions in the form of “if-then”: behavioural rules which decide what action has to be taken in a particular state. After execution of a particular “if-then” rule its outcome is used to record whether it was a good decision and this determines probability of choosing the “if-then” rule in future.

It is important to differentiate between single-agent and multi-agent *reinforcement learning*. Single-agent *reinforcement learning* is formally modelled as the Markov decision process. The Markov decision process is defined for a discrete finite set of environment states and a discrete finite set of agent’s actions. The definition also includes a state transition probability function and agent’s expected reward function [42] [43]. The state transition function and agent’s reward function (the dynamics of the system) remain *stationary* (the same) and do not vary over time. Therefore the Markov decision process has a basic property of being *stationary* [43]. Single-agent *reinforcement learning* assumes that the agent environment remains *stationary* because single-agent *reinforcement learning* is based on the Markov decision process. Furthermore, proof of convergence for single-agent *reinforcement learning* is based on the assumption that environment remains *stationary*.

The assumption of *stationary* environment does not remain valid in the case of multi-agent *reinforcement learning*. In a multi-agent system, environment of an agent contains other autonomous agents that are able to learn and adapt. If an agent environment contains even one other autonomous learning agent then the environment is *dynamic* and can undergo unpredictable changes over time. Therefore, multi-agent *reinforcement learning* must consider *dynamic* nature of an agent’s environment. Kinds of multi-agent *reinforcement learning* are discussed after single-agent *reinforcement learning*.

Single-agent Reinforcement Learning for Multi-agent Systems

Single-agent *reinforcement learning* can be extended to multi-agent systems if each agent assumes that its environment is *stationary*. However, such an extension can fail if an opponent learns from history of interactions and adapts its actions accordingly. Extensions of single-agent *reinforcement learning* for *zero-sum* and *common-payoff* games have shown more conclusive results than extensions for *general-sum* games [44]. For instance, extensions of single-agent *reinforcement learning* for *common-payoff* games have shown good results in robotic domains [45] and [46]. Authors of [47] provide insights into how single-agent *reinforcement learning* works for *common-payoff* games. However, [47] does not offer similar discussion for *zero-sum* or *general-sum* games.

A number of research papers report attempts of extending single-agent *reinforcement learning* for *general-sum* scenario of *bilateral negotiations* in multi-agent systems. In particular, genetic algorithms, Q-learning and Erev & Roth types of single-agent *reinforcement learning* (see Figure 3.1) have been tried. Some of the attempted uses of genetic algorithms, Q-learning and Erev & Roth learning for *bilateral negotiations* in multi-agent systems and differences between evolutionary, anticipatory and reactive reinforcement learning are discussed as follows.

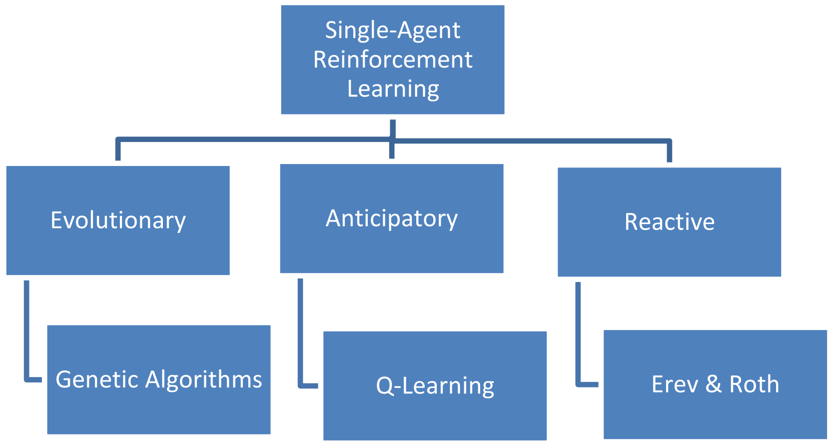

Figure 3.1 Types of Single-Agent Reinforcement Learning

Genetic Algorithms

In general, evolutionary *reinforcement learning* is useful if an agent is unable to accurately sense the state of its environment [41]. However, it has at least two main limitations. Firstly, evolutionary approach is only effective if the environment has a sufficiently small number of states [41] [48]. Secondly, an agent using evolutionary *reinforcement learning* does not learn while interacting with its environment [41] and delays learning until it has finished its interaction with the environment [48]. Methods that can capture and utilize behaviour of individual interactions can be highly efficient as compared to evolutionary methods in many applications [41], such as multi-round *bilateral negotiations*.

Genetic algorithms are a specific kind of evolutionary *reinforcement learning* as shown in Figure 3.1. A number of research papers are listed in [32] and [49] that use genetic algorithms for simulation of *bilateral negotiations*. For instance, [49] uses a genetic algorithm to simulate multi-round *bilateral negotiation* in a two agent system consisting of a seller and a buyer. The agents have *incomplete information* but *dynamic* market conditions, for instance history of *dynamic* prices in *organized* market, are not mentioned. Furthermore, only seller agent uses the genetic algorithm and buyer agent uses a *stationary* strategy during multi-round negotiation. In brief, seller agent has used genetic algorithm as a single-agent *reinforcement learning* in a *stationary* agent-based environment. Therefore, [49] is not suitable for simulation of *bilateral negotiations* in a *dynamic* environment like electricity market.

Q-Learning

Some problems are simple because agent is only concerned with immediate rewards. However, in other problems, like *bilateral negotiations*, it is also important to consider future consequences or rewards of current actions [50] in addition to immediate rewards. Therefore, an anticipatory *reinforcement learning* technique, such as Q-learning, looks promising for *bilateral negotiation* because agent wants to know the effects of its actions on future.

Q-learning was presented by Christopher Watkins in 1989 as a result of his PhD research [51] at the University of Oxford. The single-agent Q-learning is an iterative method to estimate values of environment states stored in an arbitrarily initialized table. The table is called Q-table and can represent a finite number of possible states for a particular environment. Values of visited states in the Q-table are updated after an iteration of Q-learning. The single-agent Q-learning is useful for *stationary* systems with finite states if all states can be represented in the form of a Q-Table. The single-agent Q-learning is not intended for environments that have infinite number of states or *dynamic* environments. Therefore, application of single-agent Q-learning is not suitable for environments with very large number of states because of prohibitively large storage space required for Q-table values.

A number of research papers, including [52], [53] and [54] have reported use of Q-learning for *bilateral negotiation* problem. In [52], a Q-learning algorithm is proposed for multi-round *bilateral negotiation* in e-commerce. The Q-learning algorithm is tested in a two agent system consisting of a seller and a buyer. Both seller and buyer agents use the Q-learning algorithm for *dynamic* strategies during multi-round *bilateral negotiation*. However, *dynamic* market conditions, for instance history of *dynamic* prices in *organized* market, are not considered. Furthermore, no details of Q-table implementation are available in [52]. Therefore, both agents have used the Q-learning algorithm as single-agent *reinforcement learning* in a partially *dynamic* environment. Since [52] does not consider *dynamic* market conditions, such as history of *dynamic* prices in *organized* market, it is not suitable for simulation of *bilateral negotiations* in a *dynamic* environment like electricity market.

A simplified Q-table is presented in [53] for *bilateral negotiation* of short duration transactions for only next week. A number of seller and buyer agents are included in the simulation and only seller agents learn *dynamic* strategies by single-agent Q-learning. The Q-table of a seller agent includes possibility of only four environment states and four actions are available to the seller agent. A seller agent determines state of the environment from percentage of its previously accepted offers for bilateral transactions. One of the available actions considers history of *dynamic* prices in *organized* market to set new bilateral transaction offers. Authors of [53] acknowledge that there can be many other ways of implementing Q-learning and do not claim an optimal implementation. Although [53] considers *dynamic* environment, proposed Q-table is only useful for single-round decision of repeated short-duration transactions. The Q-table cannot be helpful for multi-round *bilateral negotiations* for medium-duration transactions.

A relatively larger Q-table is presented in [54] that considers ten states of environment and ten actions available to an agent in a two agent system. The Q-table has been used for only simulating repeated multi-round *bilateral negotiations* in a market context. In general, both *bilateral negotiations* and *organized* trading exist in markets and affect each other. However, the Q-table does not capture the history of *dynamic* prices in *organized* trading on subsequent *bilateral negotiations*. In fact, the Q-table only considers *dynamic* interaction between a seller and a buyer agent during multi-round *bilateral negotiations*. The Q-table assumes that market conditions, such as prices of *organized* market, remain *stationary* throughout the simulation. Therefore, both agents have used the Q-learning algorithm as single-agent *reinforcement learning* in a partially *dynamic* environment. Since [54] does not consider history of *dynamic* prices in *organized* market, it is not suitable for simulation of *bilateral negotiations* in electricity markets.

Erev & Roth Learning

As a side note, Q-learning is compared with another learning algorithm known as Erev & Roth in [54]. Figure 3.1 shows that Erev & Roth is a kind of reactive *reinforcement learning* whereas Q-learning is a type of anticipatory *reinforcement learning*. It is shown in [54] that Erev & Roth based agents cannot learn consistent behaviour and fail to achieve sequential bargaining. In fact, Erev & Roth mostly resulted in a single-round negotiation. The single-round negotiation is analogous to use of Erev & Roth for learning to improve daily submission of hourly bids in day-ahead market simulation in AMES [25]. It is acknowledged in [25] that the use of single-agent learning in a multi-agent system does not guarantee convergence due to system dynamics. Therefore, Erev & Roth algorithm is not suitable for *bilateral negotiations* because these negotiations are multi-round endeavours.

From the above discussed applications of single-agent *reinforcement learning* it can be concluded that such approaches fail to capture effect of *dynamic* prices in *organized* market on subsequent medium-duration bilateral transactions. In addition, some of the discussed applications fall short of simulating medium-duration bilateral transactions by multi-round *bilateral negotiations*. In general, applications of single-agent *reinforcement learning* in multi-agent systems do not have solid theoretical foundations because these applications ignore the assumption of a *stationary* environment. Suitability of multi-agent *reinforcement learning* for simulation of *bilateral negotiations* is discussed as follows.

Multi-agent Reinforcement Learning

A number of multi-agent *reinforcement learning* techniques are presented in [42] for *competitive*, *cooperative* and *mixed* tasks. For each kind of task, the techniques are further divided in terms of *static* and *dynamic* environments in [42]. Discussion in this chapter restricts to *mixed* tasks in *dynamic* and *general-sum* scenarios. Figure 3.2 shows the multi-agent *reinforcement learning* techniques that are applicable to *mixed* tasks in *dynamic* and *general-sum* scenarios.

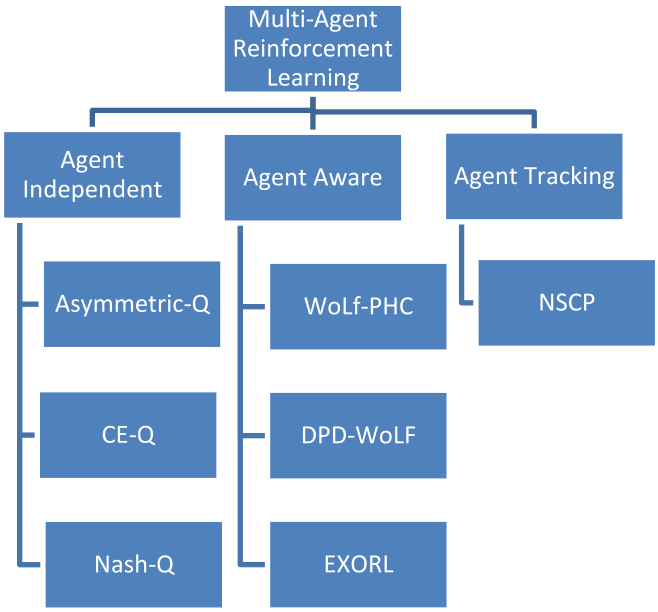

Figure 3.2 Types of Multi-Agent Reinforcement Learning Techniques for Mixed Tasks, Dynamic Environments and General-Sum Scenarios

None of the techniques shown in Figure 3.2 is reported for simulation of *bilateral negotiations* in [42]. Suitability of agent-independent, agent-aware and agent-tracking methods, in general, is discussed below for simulation of *bilateral negotiations*.

Agent-Independent Methods

These methods do not require an agent to be aware of other agents or track intentions of other agents. For that reason, these are called agent-independent methods. Agent-independent methods use game-theoretic solvers, with *complete information* about all agents, to evaluate state values and policies for all agents [42]. As a result, agent-independent approaches are not suitable for *bilateral negotiations* between agents that have *incomplete information* about each other.

Agent-Aware Methods

Agent-aware methods use heuristics to adapt to other agents but without guarantee of convergence [42]. For instance, an agent-aware method can use heuristic *behaviour-dependent strategy* for *bilateral negotiations.* As discussed in subsection 3.4.1 on Heuristic Techniques, if both agents use *behaviour-dependent strategy* and *contending* behaviour then there is risk that agent positions may not converge and consequently *bilateral negotiation* may fail. Use of an agent-aware method is not recommended, without support of additional techniques, because of non-convergence risks.

Agent-Tracking Methods

Agent-tracking methods estimate strategies of other agents to adapt appropriate responses [42]. For instance, an agent can estimate ultimate price of its opponent from interactions in multi-round *bilateral negotiations* by Bayesian learning, discussed in next section. The learning agent can then adapt its offers to get a more favourable outcome from *bilateral negotiations*. This example shows that agent-tracking methods can facilitate *bilateral negotiations* between agents having *incomplete information* about each other.

3.4.2.2 Supervised Learning

In *supervised learning*, an agent generally learns from examples in a set of training inputs and outputs provided by an intelligent supervisor. For example, Neural Networks that are composite models of supervised learning (see Figure 3.3) are useful for *supervised learning* in pattern recognition etc. However, an agent with *incomplete information* may itself learn from examples of its interaction with an opponent by *supervised learning*. For instance, a *supervised learning* agent can estimate types or intentions of its opponents in *bilateral negotiations*. Bayesian classifier and Bayesian learning are basic and advanced models (see Figure 3.3) of *supervised learning* that are useful for simulating *bilateral negotiations* in multi-agent systems. These two techniques are discussed in the following two subsections.

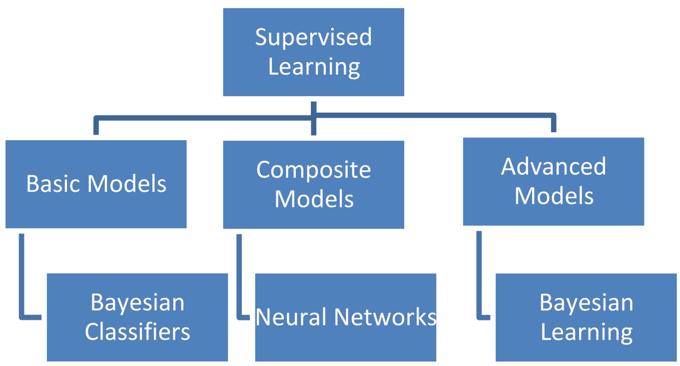

Figure 3.3 Kinds of Supervised Learning

Bayesian Classifiers

Bayesian classifiers are a kind of basic models of *supervised learning* (see Figure 3.3). Bayesian classifiers are based on Bayes' rule. Bayes' rule uses new information samples and prior probability to determine a posterior probability. In other words, Bayes' rule estimates how to update own beliefs in the light of new information. Interestingly, Bayes' rule does not recommend what our beliefs should be, it only suggest how to update existing beliefs. Initially, Bayes' rule uses an assumed prior probability and information samples from previous two interactions. After determining initial posterior probability, it is used as prior probability during next round of interaction.

In [40], an agent uses a simplified Bayesian classifier to classify opponent behaviour in multi-round *bilateral negotiations*. In each round, the Bayesian classifier determines if opponent behaviour is *yielding*, *contending* or *linear*. Then, agent uses latest information about its opponent to adapt its own behaviour while *bilateral negotiation* is in progress.

Bayesian Learning

Before discussing applications of Bayesian learning, it is important to differentiate it from belief networks (Bayesian networks) or learning belief networks. Belief networks are also called Bayesian networks because belief networks can represent a particular assumption of Bayesian learning. A belief network is an acyclic directed graph constructed by a diagnostic expert. Belief networks can be used for reasoning under uncertain circumstances to diagnose faults or disease etc. However, belief networks may not provide accurate models. Learning belief networks can be used instead of belief networks to avoid inaccurate models. In addition, a learning belief network is useful to learn a network from diagnostic data.

Like Bayesian classifiers, Bayesian learning is also based on Bayes' rule. However, Bayesian learning uses Bayes' rule for more sophisticated applications as compared to Bayesian classifiers. For instance, Bayesian learning can estimate private intentions of opponents from information revealed during interactions. By comparison, a Bayesian classifier can simply determine type of opponent's behaviour.

ultimate price of negotiating opponent is estimated by Bayesian learning in [49] and [55]. In each round of multi-round *bilateral negotiation*, experience of interacting with opponent is used to update estimated belief of its ultimate price.

3.5 Simulation Techniques for Financial Transmission Instruments

This discussion is limited to simulations of FTR auction or risk constrained FTR bidding because no research paper was found on simulation of ARR allocation. Agent-based simulation of FTR bidding and auction is presented in [56] and [57].

Both [56] and [57] provide detailed modelling of simulated FTR markets that determine a market clearing price. FTR bid quantities are assumed to be fixed at specified levels without reasoning in [56] and [57]. Moreover, FTR bid prices are initialized equal to the difference between LMPs at source and sink of FTR in both [56] and [57]. In [57], however, simulation is repeated under *stationary* conditions and a naïve reinforcement learning method is used to adjust initial FTR bid prices by simple decision rules.

In [58], FTR bid quantities are determined by maximum available FTR quantities posted by ISO. However, a method is presented for risk analysis of FTRs and FTR bid prices are chosen according to a risk-constrained bidding strategy and the difference between expectation of LMPs at source and sink of FTR. It is assumed that an FTR bidder has incomplete information models of its opponents but all opponents' bidding strategies remain *stationary*. The bidder uses Bayesian Nash equilibrium to solve the incomplete information game. The game theoretic approach assumes that a bidder is optimizing its bids in a *stationary* environment. However, an appropriate risk analysis method can be developed and deployed in an agent-based environment to incorporate *dynamic* bidding strategies of all FTR bidding agents.

3.6 Conclusions

Due to assumption of *complete information*, game-theoretic models are not appropriate for simulation of bilateral transactions among multiple participants with *incomplete information*. Agent-based models allow bilateral interaction between multiple participants under *incomplete information*. Furthermore, open source software vis-á-vis proprietary software provide open-access and detailed understanding of implemented model. It is possible to modify and extend open source software for specific research and training needs. AMES is open source agent-based simulation software that already models a day-ahead market for auction of energy. Therefore, this research work builds on AMES by incorporating models of bilateral transactions and financial transmission instruments.

Some *match making* simulation techniques ignore *transmission constraints*, assume *complete information* or work for *organized* bilateral transactions. However, existing portfolio optimization methods can be extended to accommodate *transmission constraints* and used in agent-based systems. The extended portfolio optimization procedures will enable simulation of *match making* for *direct-search* bilateral transactions under *incomplete information*.

Heuristic techniques, like *time-dependent strategy*, are simple but useful for simulation of *bilateral negotiation*. However, if both agents use *behaviour-dependent strategy* and *contending* behaviour then there is risk that agent positions may not converge and consequently *bilateral negotiation* may fail. Applications of single-agent *reinforcement learning* fail to capture effects of *dynamic* prices in *organized* markets on subsequent medium-duration bilateral transactions. Moreover, uses of single-agent *reinforcement learning* in multi-agent systems do not have solid theoretical foundations because of assuming a *stationary* environment.

Agent-tracking methods are a kind of multi-agent *reinforcement learning* and suitable for *dynamic* environment. These methods estimate models of other agents' *dynamic* policies and adapt some kind of best response to the estimated policies. Therefore, agent-tracking approach has potential to lead to successful *bilateral negotiations* between agents that have *incomplete information* about each other. In general, a *supervised learning* agent can estimate type or intentions of its opponents in *bilateral negotiations*. In particular, Bayesian learning type of *supervised learning* can estimate private intentions of opponents from information revealed through interactions during *bilateral negotiations*.

Interestingly, Bayesian learning provides a way to respond to opponent behaviour while avoiding risks of *behaviour-dependent strategy*. Bayesian learning can play an auxiliary role by supporting a main negotiation strategy, like *time-dependent strategy*. Additionally, if Bayesian learning is followed by an appropriate response to opponent's estimated strategy then it can also reap benefits of agent-tracking approach in multi-agent *reinforcement learning*.

In this thesis, existing portfolio optimization methods will be extended to accommodate *transmission constraints* and used in multi-agent systems. The extended portfolio optimization procedures will enable simulation of *match making* for *direct-search* bilateral transactions under *incomplete information*. Determination of a bilateral trade's utility, over a range of negotiable prices, by match making algorithm will enable development of a utility-based bilateral negotiation strategy. Following Bayesian learning to discover an opponent's estimated strategy, an appropriate response will be developed to support the utility-based strategy.

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4 Model of Simulated Electricity Market

4.1 Introduction

In practical power systems, power flows over transmission network from sellers to buyers. In response, buyers transfer money to sellers through financial system. In addition, a number of data-flows and decision processes take place to support different operations in real world markets. By comparison, only decision processes and data-flows exist in simulated electricity market environments. This chapter outlines a brief description of electricity market model used in FABS.

Decision processes are vital elements of the simulated market operations in FABS. In addition to decision processes, data-flows are crucial components of simulated market operations in FABS. A decision process allows a market participant or independent system operator (ISO) to determine best course of action in a simulated market operation. Market participants in FABS are of two types: Generation Companies (GenCos) who are sellers of bulk-energy; and Load Serving Entities (LSEs), who are buyers of bulk-energy. In this thesis, data-flows serve following purposes. A data-flow carries inputs to each decision process that is undertaken by ISO or a market participant. A separate data-flow carries outputs of each decision process of ISO or a market participant. Moreover, data-flows support communication among market participants and ISO to convey results of their decision processes.

A flowchart (shown in Figure 4.1) indicates sequence of decision making processes of different market participants and ISO. In addition, the flowchart illustrates data-flows that carry inputs and outputs of the decision processes as well as data-flows for communication between the market participants. Moreover, brief general descriptions of the data-flows are given in Table 4.1. Components of every data-flow are illustrated by a separate figure and the figure numbers are listed in Table 4.1. The simulated market operations are discussed with help of graphical representations of components in each data-flow. Use of outputs of one simulated market operation as inputs in subsequent operations is highlighted to clarify sequence and links between market operations. Therefore, only inputs to and outputs of decision processes are presented in this chapter, while details of how inputs are processed to compute outputs are presented in chapters to follow.

Legend of Figure 4.1 is explained in this paragraph. As indicated in the legend, data-flows are represented by arrows and decision processes by boxes. Decision processes of ISO, individual decision processes of participants and bilateral decision processes of participants are represented by distinct shapes, as shown in the legend of Figure 4.1. Blue, red and green colours represent decision processes of GenCos, LSEs and ISO respectively. Data-flows have large number of components, making it difficult to list all these components on the flowchart. Therefore, alphabetical data-flow markers, listed in Table 4.1, are used in the flowchart. Naming convention of alphabetical order of data-flow markers is explained in the next paragraph.

Each data-flow is designated with a capital alphabet alone or a capital alphabet with a subscript, as illustrated in Figure 4.1. The capital letter indicates order of the corresponding data-flow in the overall sequence of data-flows and decision processes. For instance, ISO's decision process for annual ARR allocation takes place after data-flow A (inputs to ARR allocation decision process) and before data-flow B (outputs of ARR allocation decision process). Moreover, a pair of data-flow markers containing same capital letter, e.g. C_g and C_l, represents a pair of concurrent data-flows. The subscript (g or l) in a data-flow marker indicates type of corresponding market participant; g for a GenCo and l for an LSE. For example, ISO simultaneously communicates results of annual ARR allocation to both types of market participants. Thus, data-flow C_g and data-flow C_l take place concurrently.

FABS is developed in Java but Matlab functions are used for decision processes of Annual FTR Bids, Annual FTR Auction and Annual Match Makings (see Figure 4.1). However, all other decision processes take place within Java environment. Input data for a decision process in Matlab environment is sent form Java to Matlab – indicated by data-flow markers with superscript J2M in Figure 4.1. After the decision process is over in Matlab, its output data is retrieved from Matlab environment to

Java based FABS – indicated by data-flow markers with superscript M2J in Figure 4.1.

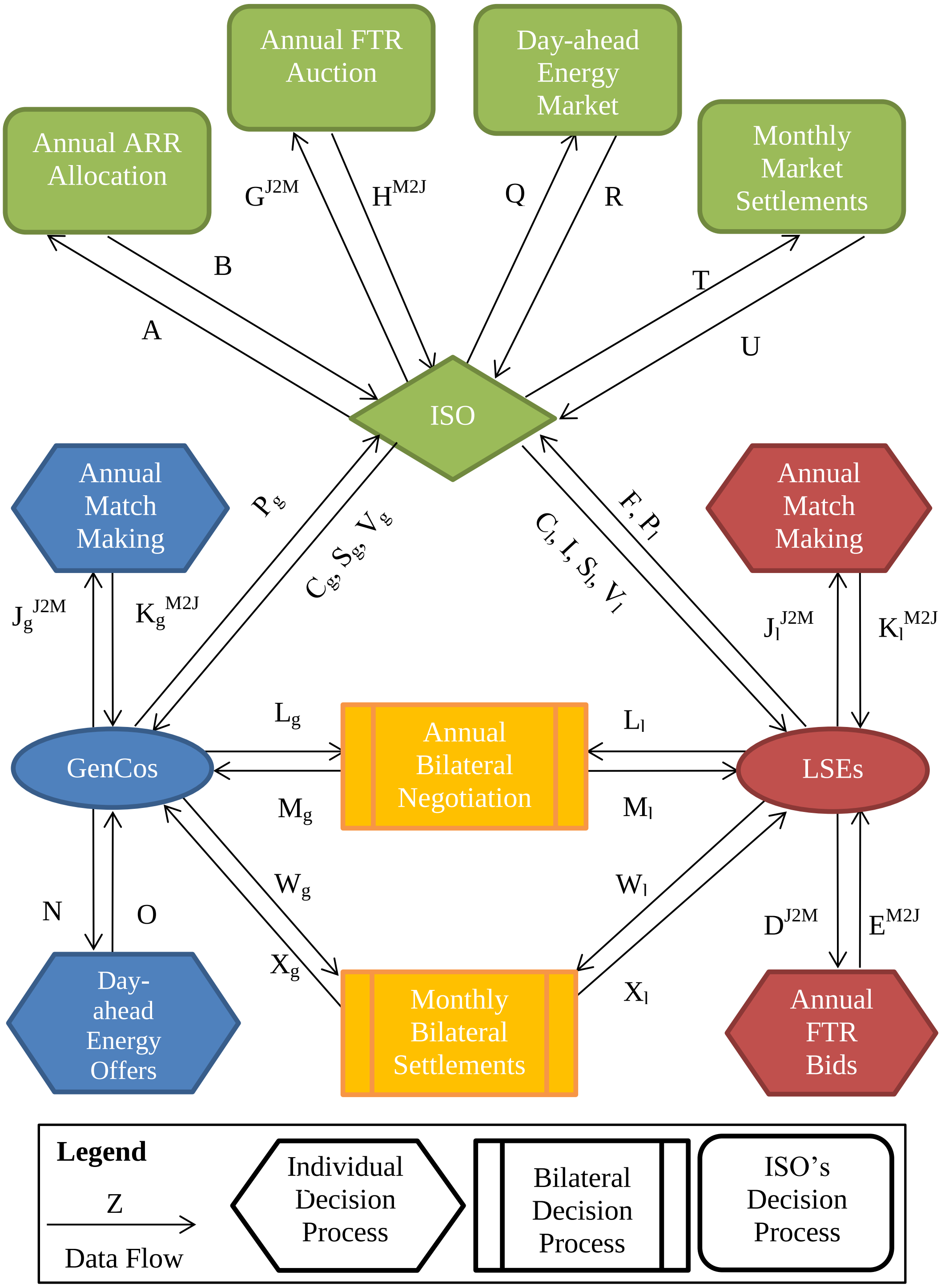

Figure 4.1 Overall Graphical Representation of Decision Processes and data-flows in the Simulated Market Operations

Table 4.1 Purposes and References to Components of Data Flows for All Simulated Market Operations

Data Flow Marker	**Purpose of Data Flow**	**Figure Showing Components of Data Flow**
A	ISO's inputs to its decision process for annual ARR allocation	Figure 4.2
B	ISO's Outputs of its decision process for annual ARR allocation	Figure 4.3
C_l	Communication of annual ARR allocation results from ISO to LSEs	Figure 4.4
C_g	Communication of annual ARR allocation results from ISO to GenCos	Figure 4.5
D	An LSE's inputs to its decision process for optimal annual FTR bidding	Figure 4.6
E	An LSE's outputs of its decision process for optimal annual FTR bidding	Figure 4.7
F	Communication of optimal FTR bids from LSEs to ISO	Figure 4.8
G	ISO's inputs to its decision process for annual FTR auction	Figure 4.9
H	ISO's outputs of its decision process for annual FTR auction	Figure 4.10
I	Communication of annual FTR auction results from ISO to each LSE	Figure 4.11

Data Flow Marker	**Purpose of Data Flow**	**Figure Showing Components of Data Flow**
J_g	A GenCo's inputs to its portfolio optimization based match making decision process for annual Financial Bilateral Transactions	Figure 4.12
J_l	An LSE's inputs to its portfolio optimization based match making decision process for annual Financial Bilateral Transactions	Figure 4.13
K_g	A GenCo's outputs of its portfolio optimization based match making decision process for annual Financial Bilateral Transactions	Figure 4.14
K_l	An LSE's outputs of its portfolio optimization based match making decision process for annual Financial Bilateral Transactions	Figure 4.15
L_g	A GenCo's inputs to the decision process of annual bilateral negotiation with an LSE	Figure 4.16
L_l	An LSE's inputs to the decision process of annual bilateral negotiation with a GenCo	Figure 4.17
M_g	A GenCo's outputs of the decision process of annual bilateral negotiation with an LSE	Figure 4.18
M_l	An LSE's outputs of the decision process of annual bilateral negotiation with a GenCo	Figure 4.19
N	A GenCo's inputs to its decision process for optimal hourly price-sensitive supply offers	Figure 4.20
O	A GenCo's outputs of its decision process for optimal hourly price-sensitive supply offers	Figure 4.21

Data Flow Marker	Purpose of Data Flow	Figure Showing Components of Data Flow
P_l	Communication of bids, and other data for day-ahead energy market, from each LSE to ISO	Figure 4.22
P_g	Communication of offers, and other data for day-ahead energy market, from each GenCo to ISO	Figure 4.23
Q	An ISO’s inputs to its decision process for clearing day-ahead energy market	Figure 4.24
R	An ISO’s outputs of its decision process for clearing day-ahead energy market	Figure 4.25
S_l	Communication of day-ahead energy market clearing results from ISO to LSEs	Figure 4.26
S_g	Communication of day-ahead energy market clearing results from ISO to GenCos	Figure 4.27
T	An ISO’s inputs to its decision process for market settlements of energy, FTRs and ARRs	Figure 4.28
U	An ISO’s outputs of its decision process for market settlements of energy, FTRs and ARRs	Figure 4.29
V_l	Communication of market settlements’ results of energy, FTRs and ARRs from ISO to each LSE	Figure 4.30
V_g	Communication of market settlements’ results for energy from ISO to each GenCo	Figure 4.31
W_g	A GenCo’s inputs to the decision process of monthly bilateral settlement with an LSE	Figure 4.32

Data Flow Marker	Purpose of Data Flow	Figure Showing Components of Data Flow
W_l	An LSE's inputs to the decision process of monthly bilateral settlement with a GenCo	Figure 4.33
X_g	A GenCo's outputs of the decision process of monthly bilateral settlement with an LSE	Figure 4.34
X_l	An LSE's outputs of the bilateral decision process of monthly bilateral settlement with a GenCo	Figure 4.35

Market operations in FABS repeat on annual, monthly or daily basis, as explained next. ARR allocation, FTR auction and decision making for Financial Bilateral Transactions are annual operations. A settlement of organized and bilateral electricity trades takes place monthly. Optimization of offers for day-ahead auction and clearing of day-ahead auction are daily operations. In FABS, each simulation year has 12 months, each month has 30 days and each day has 24 hours. Annual operations take place at the beginning of each simulation year. Thereafter daily operations of day-ahead market take place before start of actual day of delivering electricity. Contrary to annual and daily operations, monthly operations take place at the end of each month. Therefore, electricity market operations in FABS are discussed in order of annual, daily and monthly operations in Sections 4.2, 4.3 and 4.4 respectively. Conclusions of this Chapter are presented in Section 4.5.

4.2 Annual Sequence of Simulated Market Operations

Discussion of annually simulated market operations deal with bilateral trades and can be divided into two main parts: (i) operations for financial transmission instruments and (ii) operations for Financial Bilateral Transactions.

4.2.1 Annual Operations for Financial Transmission Instruments

Financial Transmission Rights (FTR) and *Auction Revenue Rights* (ARR) are collectively called *financial transmission instruments*. The *financial transmission instruments* support energy trading because they provide hedges against specific risks in electricity markets. By definition, a *Financial Transmission Right* (FTR) is a financial instrument that can hedge transmission congestion cost of a market participant. An *Auction Revenue Right* (ARR) is defined as a financial instrument that can hedge the cost of acquiring a Financial Transmission Right.

In FABS, annual sequence of market operations starts with ISO's allocation of Auction Revenue Rights to LSEs. FABS restricts allocation of ARRs only to LSEs because in most practical markets only LSEs are eligible to bid for auctions of FTRs. It is important to note that no ARR payments are made to LSEs at the time of ARR allocation. Allocated ARRs are valued according to subsequent market clearing prices of FTR auction, as explained in Chapter 5. The following paragraph explains reasons of conducting ARR allocation before FTR auction in FABS.

As mentioned in Chapter 2, practical electricity markets include multi-round annual and monthly auctions of FTRs, as well as multi-stage annual allocation of ARRs. In addition to buying FTRs in the initial round of annual auction, participants can also adjust their investments in FTRs by selling spare FTRs and buying additional FTRs in subsequent rounds of annual auction. Participants of real world markets can also adjust their investments in FTRs by buying or selling in monthly FTR auctions.

This thesis focuses on optimal strategies of market participants for: (i) securing direct-search Financial Bilateral Transactions and (ii) competitively obtaining Financial Transmission Rights. Therefore, a detailed model of an LSE's optimization of its FTR bids is included in FABS, as explained in 4.2.1.2. However, since ISO's decision making for ARR allocation and FTR auction is not a primary concern of this research, extensive modelling and simulation of ARR allocation and FTR auction is beyond the scope of this thesis. Thus, FABS only includes simplified models of both financial transmission instruments as explained next. The simplified models of financial transmission instruments are a single-round annual FTR auction and a single-stage annual ARR allocation. The single-round annual FTR auction in FABS allows a one-off purchase of required year-long FTRs, for the coming one year, but does not facilitate any subsequent sale or purchase of the FTRs. This inflexibility forces market participants to carefully choose their annual FTR bid quantities. Since ARRs can hedge the cost of acquiring FTRs, it is assumed that market participants in FABS use allocated ARRs to determine FTR bid quantities. For that reason, ARR allocation is carried out before FTR auction in FABS.

Annual operations for financial transmission instruments take place at the beginning of each simulation year in FABS. The annual operations for financial transmission instruments involve the ten data-flows marked as A to I in Figure 4.1. Moreover, the figure shows that the annual operations include three decision processes: (i) allocation of ARRs by ISO; (ii) optimization of FTRs bids by LSE; and (iii) auction of FTRs by ISO. Sequence of these data-flows and decision processes is reflected by alphabetical order of the data-flow markers.

4.2.1.1 Annual Allocation of Auction Revenue Rights by ISO

Initiation of annual ARR allocation process by ISO is starting point of annual simulation in FABS, indicated by data-flow A in Figure 4.1. ISO needs components of data-flow A, illustrated in Figure 4.2, as inputs to its decision process for annual ARR allocation. All inputs, shown in Figure 4.2, are internally available to ISO in the form of system or market data. History of LMPs and peak load distribution in the previous year are market data. Generator capacities, line capacities, power transfer distribution factors and locations of source and sink nodes are system data of ISO.

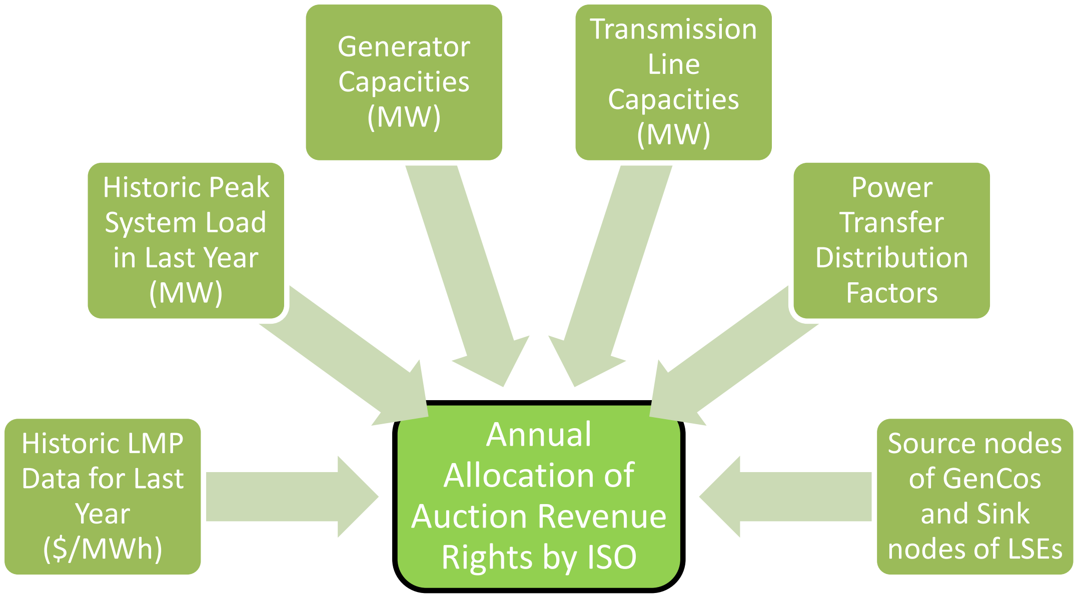

Figure 4.2 Components of Data Flow A: ISO's Inputs to its Annual Allocation of Auction Revenue Rights

Details of a mathematical framework for the allocation of ARR by ISO are provided in Chapter 5. In addition to ARR allocation, this decision process determines upper limits of simultaneously feasible Financial Bilateral Transactions. Therefore, outputs of this decision process include allocated ARRs, simultaneously feasible Financial Bilateral Transactions and source and sink nodes of both decision variables. These three outputs of the decision process are components of data-flow B, shown in Figure 4.3. Source and sink nodes represent local nodes of GenCos and LSEs respectively. ISO ensures that allocated annual ARRs are not only simultaneously feasible but also consistent with history of LSEs peak use of transmission system during the last year. Since ARR allocation inherently checks simultaneous feasibility, it is assumed that ISO announces allocated ARR quantities as maximum feasible Financial Bilateral Transactions.

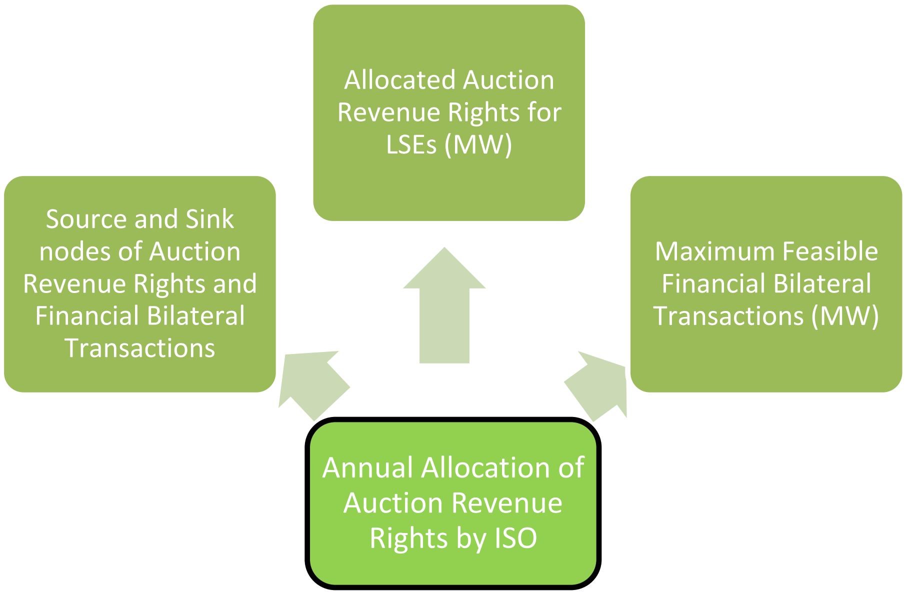

Figure 4.3 Components of Data Flow B: ISO's outputs of its Annual Allocation of Auction Revenue Rights

ISO communicates results of annual ARR allocation to LSEs and GenCos, indicated in Figure 4.1 as data-flow C_l and data-flow C_g, respectively. Figure 4.4 illustrates that data-flow C_l has three components: (i) allocated Auction Revenue Rights, (ii) maximum feasible Financial Bilateral Transactions and (iii) source and sink nodes for the revenue rights and the bilateral transactions. However, Components of data-flow C_g, illustrated in Figure 4.5, only include maximum feasible Financial Bilateral Transactions and source and sink nodes of these transactions because, in FABS, ISO does not allocate Auction Revenue Rights to GenCos.

Every LSE considers its allocated Auction Revenue Rights during its FTR bid optimization, as explained in section 4.2.1.2. ISO's announcement of maximum feasible bilateral transactions is useful for both LSEs and GenCos in match making for Financial Bilateral Transactions, as discussed in section 4.2.2.1. Although announced Financial Bilateral Transactions are simultaneously feasible under normal operating conditions, ISO may have to reduce them in case of unforeseen generation and transmission failures. However, the methodology and tool proposed in this thesis does not model these additional bilateral trade reductions.

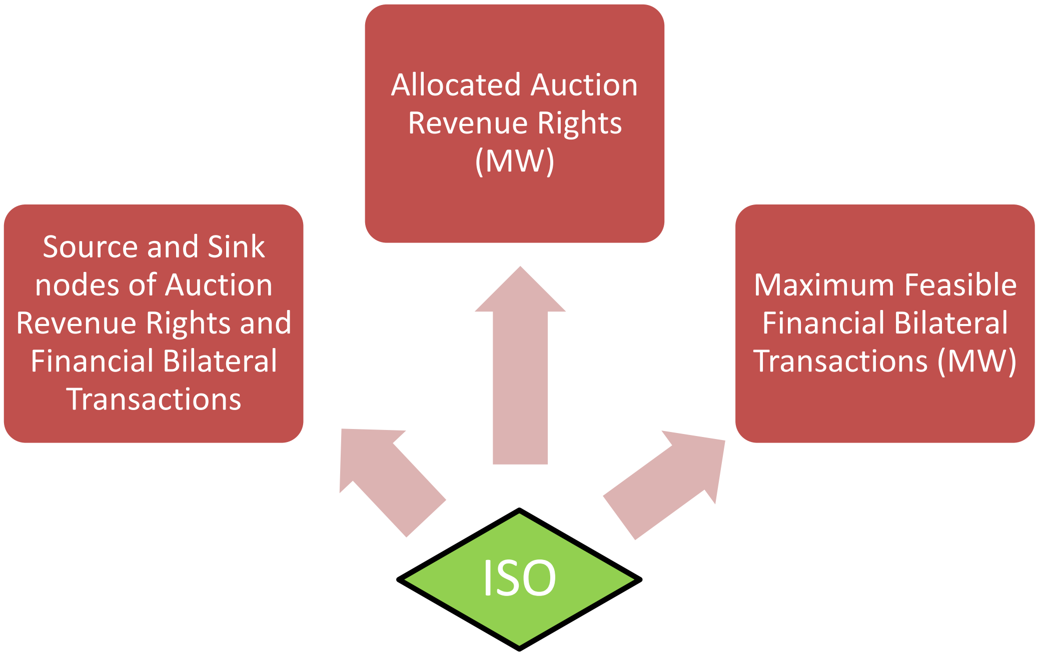

Figure 4.4 Components of Data Flow C_l: Communication of annual ARR allocation results from ISO to LSEs

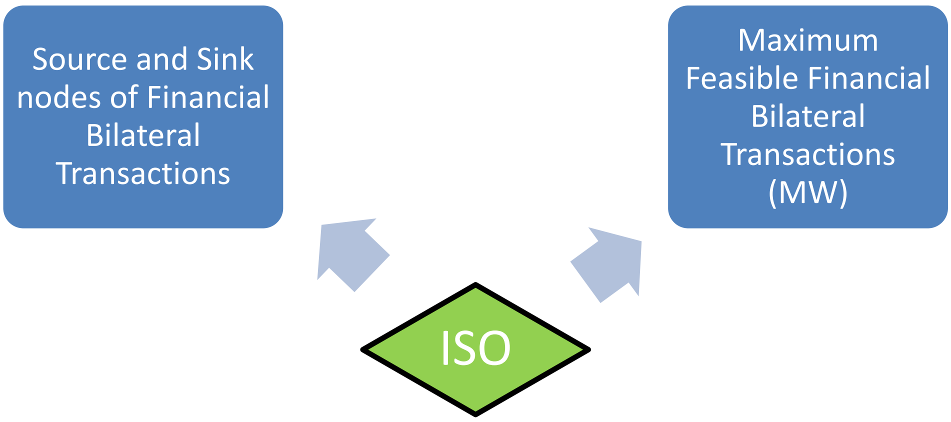

Figure 4.5 Components of Data Flow C_g: Communication of annual ARR allocation results from ISO to GenCos

4.2.1.2 Annual Optimization of its Financial Transmission Rights Bids by Every LSE

Figure 4.1 shows that LSEs optimize their bids for FTR auction after annual allocation of ARRs. Optimization of FTR bid prices is crucial for an LSE because its FTR acquisition cost is not fully recoverable if its allocated ARRs are less than its FTR bid quantities. Difference between LMPs of day-ahead market at sink and source nodes determines value of FTRs held by LSEs. LMPs of day-ahead market can unpredictably fluctuate over a large range on daily basis. Therefore, an LSE's revenue from holding an FTR can also vary from day to day. Research work to-date, presented in last chapter, used difference between expected LMPs of day-ahead market at sink and source nodes to calculate FTR bid price. In other words, only expected return for risky FTR investment was considered in the previous work. However, a new method of determining FTR bid price is used in this thesis for all risky FTR investments between the sink node of LSE and the source nodes of GenCos. The novel method incorporates variance and covariance of returns as well as private risk-aversion factor of an LSE. Incorporation of the additional data facilitates risk assessment based decision making for investment in year-long FTRs in FABS.

An LSE needs inputs shown in Figure 4.6 to optimize its own FTR bids. It needs history of LMPs and self-determined private risk aversion factor, as well as ISO-determined base load, allocated ARRs and source and sink nodes. Details of mathematical framework for optimization of its bids by an LSE, before submission to ISO, are provided in Chapter 5. Figure 4.7 shows three outputs of an LSE's effort to optimize FTR bids: (i) source and sink nodes of FTRs, (ii) bid prices of FTRs and (iii) bid quantities of FTRs. An LSE determines its bid prices by above mentioned new method which incorporates a risk assessment of holding the FTRs. An LSE's bid quantities of FTRs depend on its base load and allocated ARRs, as explained in Chapter 5. The three outputs of an LSE's effort to optimize FTR bids, data-flow E, are communicated to ISO by data-flow F, as can be seen in Figure 4.1. As a result, data-flow F has the same three components (shown in Figure 4.8) as the above mentioned three components of data-flow E (shown in Figure 4.7).

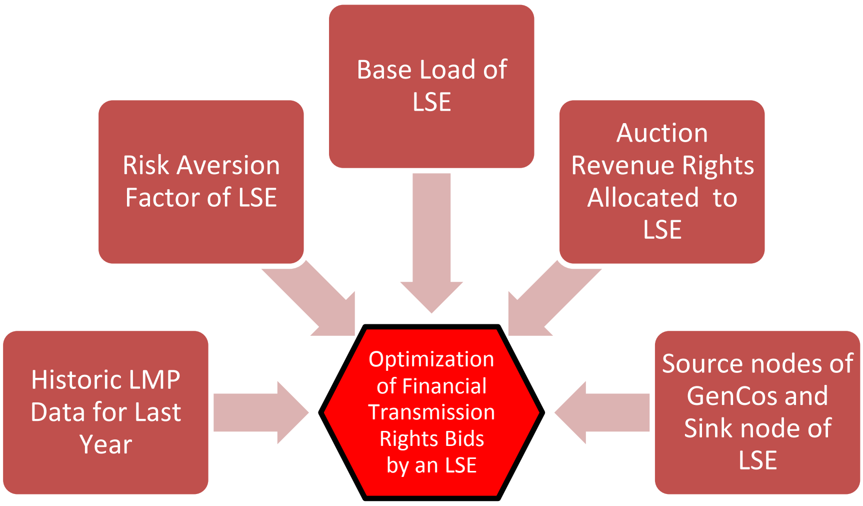

Figure 4.6 Components of Data Flow D: Inputs to Optimization of its Financial Transmission Rights Bids by an LSE

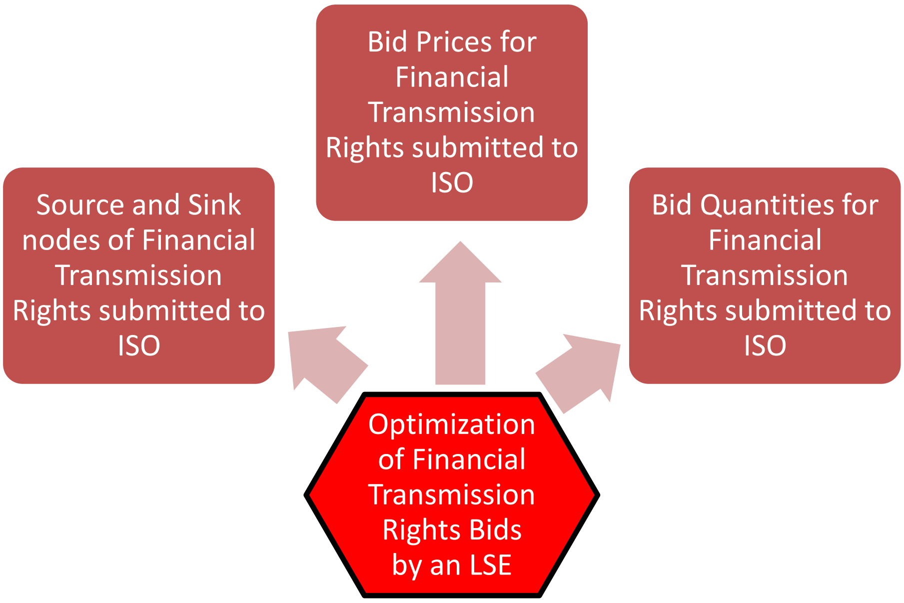

Figure 4.7 Components of Data Flow E: Outputs of Optimization of its Financial Transmission Rights Bids by an LSE

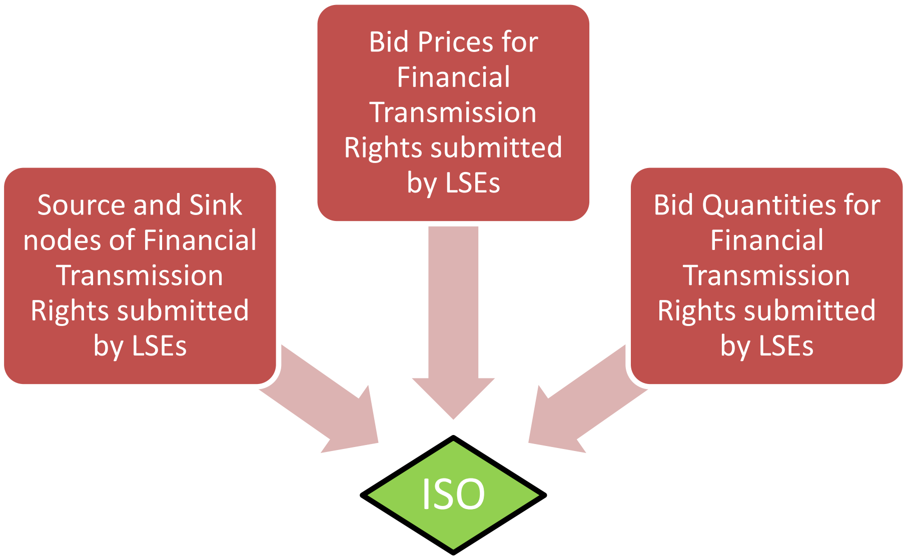

Figure 4.8 Components of Data Flow F: Communication of FTR bids from LSEs to ISO

4.2.1.3 Annual Auction of Financial Transmission Rights by ISO

As mentioned earlier, *Financial Transmission Right* is a financial instrument that can hedge transmission congestion cost of a market participant. Figure 4.9 shows ISO's inputs to optimization of annual FTR auction. The three components in communication of an LSE's FTR bids (illustrated in Figure 4.8) are included as inputs in Figure 4.9. In addition, ISO needs system data of power transfer distribution factors and transmission capacities. In FABS, ISO awards annual FTRs for full capacity of transmission lines in a single-round. ISO tackles optimization problem of annual FTR auction by means of a linear programming solver in FABS. Mathematical details of FTR auction optimization by ISO are provided in Chapter 5. Figure 4.10 illustrates that optimal solution of annual FTR auction determines source and sink nodes as well as quantities and prices of FTRs awarded by ISO to LSEs.

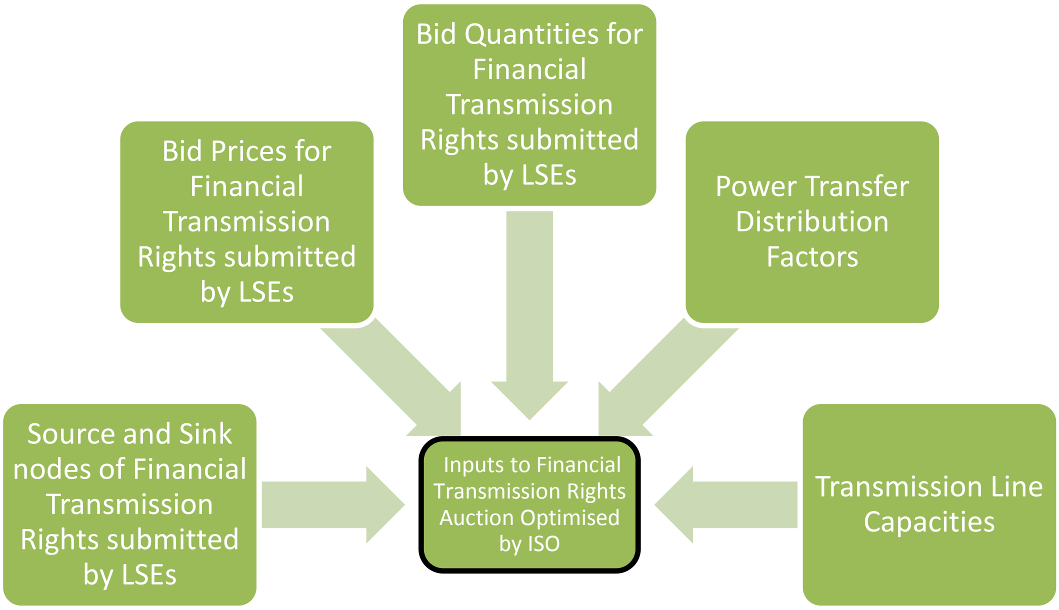

Figure 4.9 Components of Data Flow G: ISO's inputs to Optimization of Financial Transmission Rights Auction

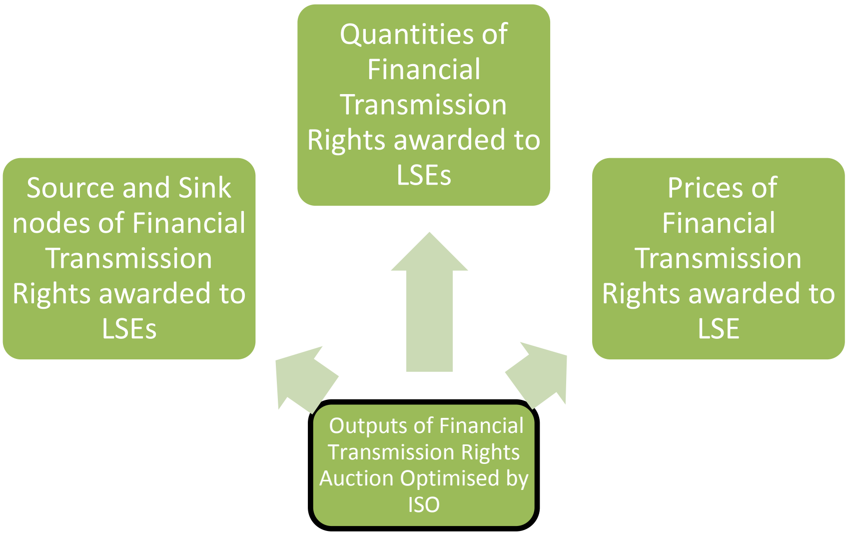

Figure 4.10 Components of Data Flow H: ISO's outputs of Optimizing Financial Transmission Rights Auction

ISO communicates results of annual FTR Auction to LSEs, indicated in Figure 4.1 as data-flow I. Figure 4.11 shows three components of data-flow I: (i) source and sink nodes of FTRs awarded to LSEs, (ii) quantities of FTRs awarded to LSEs and (iii) prices of FTRs awarded to LSEs.

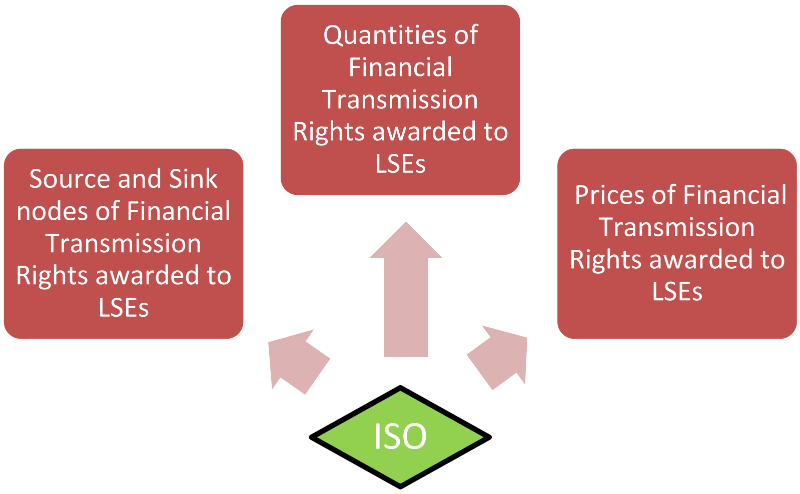

Figure 4.11 Components of Data Flow I: Communication of annual FTR Auction results from ISO to LSEs

4.2.2 Annual Operations for Financial Bilateral Transactions

Annual operations for Financial Bilateral Transactions take place after annual operations for financial transmission instruments in FABS. *Financial bilateral transactions* are contracts for transfer of financial responsibility for energy (not physical flow of energy) between buyers and sellers. The transfer of financial responsibility for energy means that buyers will be responsible for payments of agreed energy prices to sellers, as well as transmission congestion charges to ISO. First phase in the decision making of Financial Bilateral Transactions is called *match making* and involves finding suitable partners. Second phase in the decision making is multi-round *bilateral negotiations* for Financial Bilateral Transactions. The annual operations for financial transmission instruments involve the eight data-flows, marked from J_g and J_l to M_g and M_l in Figure 4.1. Moreover, the figure shows that the annual operations include three types of decision processes: (i) math making by each LSE; (ii) match making by each GenCo; and (iii) bilateral negotiations between GenCos and LSEs. Note that sequence of these data-flows and decision processes is reflected by alphabetical order of the data-flow markers.

4.2.2.1 Match Making for Financial Bilateral Transactions

In modern electricity markets like MISO, annual ARR allocation and FTR auction follow a well-defined calendar. In FABS, it is assumed that allocated ARRs and auctioned FTRs come into effect ten business days after announcement of the FTR auction results. It can be expected that, even in a decentralized market, some kind of a bilateral transaction protocol becomes an industry wide standard over time. It is assumed that market participants of FABS have a consensus on a bilateral transaction protocol and according to the protocol LSEs start the negotiation process and GenCos respond. Since FTRs financially hedge uncertain congestion costs, results of annual FTR auction can influence LSEs' yearly decision making for Financial Bilateral Transactions. Therefore LSEs undertake the yearly decision making after ISO announces results of annual FTR auction. According to the protocol in FABS, market participants have a prior agreement to restrict their offers and bids to publicly known negotiable price ranges. Furthermore, the protocol assumes that participants complete their decision making for Financial Bilateral Transactions within the ten business days after the announcement of the FTR auction results.

Day-ahead auction carries risks like sudden price spikes and investment in appropriate Financial Bilateral Transactions can hedge such risks in advance. Therefore, decision making for investment in year-long Financial Bilateral Transactions can be improved by proper risk management. In FABS, each GenCo and LSE achieves decentralized match making by determining its own optimal investment portfolio. The *portfolio optimization* provides a systematic way of exploring all available investment options for Financial Bilateral Transactions throughout the market. Furthermore *portfolio optimization* achieves systematic decentralized match making, instead of some random match making process or match making by a centralized or organized broker/bulletin-board. As discussed in chapter 3, Markowitz's modern portfolio theory [1], is useful to find an optimal portfolio under uncertainty and keep risk at a desired level. In FABS, LSEs and GenCos use maximum simultaneously feasible bilateral transactions, determined and publicly announced by ISO, in their private match making decision processes. All GenCos and LSEs concurrently determine their own course of action depending on private goals and risk preferences as well as market history.

Portfolio optimization procedures and resulting match making algorithms developed for both GenCos and LSEs have contributed to knowledge by modelling a transmission network with physical limitations on power flows through transmission lines. A match making algorithm enables a market participant to determine its private utility of each bilateral trade. Utility of a bilateral trade depends on its expected return, variance of return and risk aversion level of market participant.

Use of portfolio optimization as a decentralized match making tool for GenCos and LSEs is explained in detail in Chapter 6. However, a graphical overview of inputs and outputs of the match making algorithms of GenCos and LSEs is provided here. Components of data-flow J_g, illustrated in Figure 4.12, are inputs to a GenCo's decision process of match making for Financial Bilateral Transactions. The inputs include: (i) mutually agreed transaction protocol; (ii) history of LMPs as market data; (iii) self-determined private risk aversion factor, generation capacity and fuel consumption coefficients; (iv) base load requirement furnished by local LSE and (v) ISO-determined maximum feasible Financial Bilateral Transactions between source and sink nodes. Figure 4.13 illustrates components of data-flow J_l that are inputs to an LSE's decision process of match making for Financial Bilateral Transactions. The inputs include: (i) mutually agreed transaction protocol; (ii) history of LMPs as market data; (iii) self-determined private risk aversion factor, flat-rate agreed with retail loads; (iv) generation capacity furnished by local GenCo and (v) ISO-determined base-load requirement of the LSE, maximum feasible Financial Bilateral Transactions and FTRs between source and sink nodes. Note that data-flow J_l contains FTRs held by an LSE whereas data-flow J_g includes no FTRs because GenCos hold none in FABS.

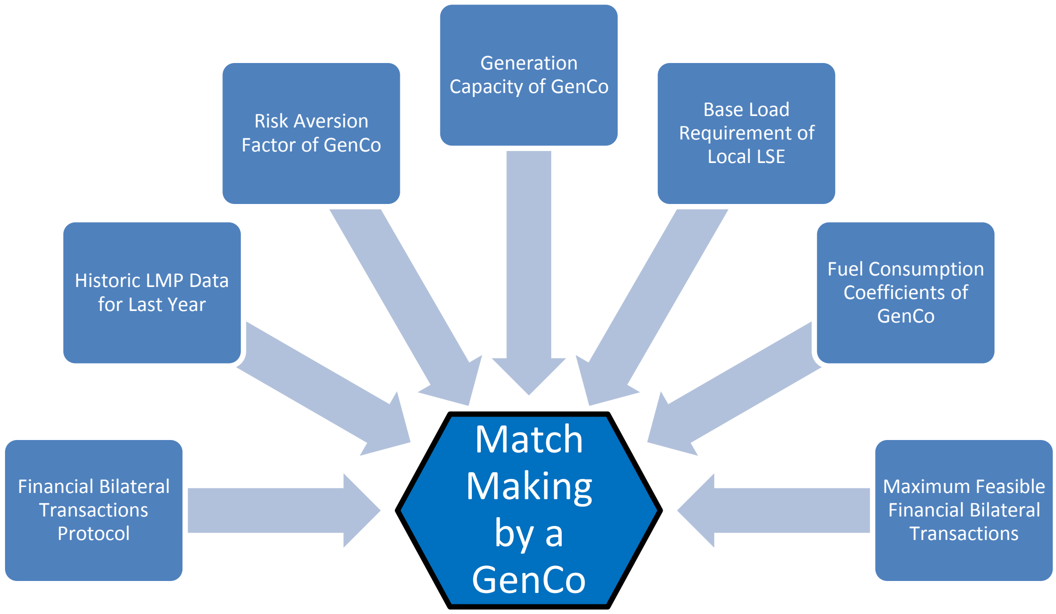

Figure 4.12 Components of Data Flow J_g: Inputs to Match Making by a GenCo

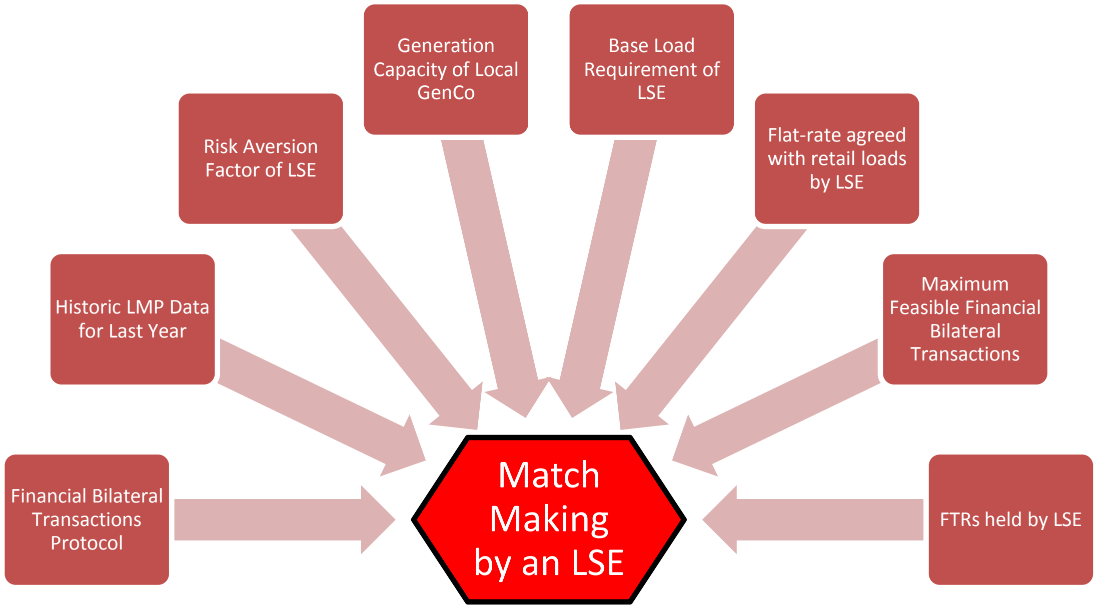

Figure 4.13 Components of Data Flow J_l: Inputs to Match Making by an LSE

The outputs of a GenCo's decision process for match making are shown in Figure 4.14 as components of data-flow K_g. As a result of its match making, over negotiable price ranges, a GenCo determines utilities of its bilateral transactions and power quantity offers for matched LSEs. Similarly, an LSE's match making over negotiable price ranges finds utilities of its bilateral transactions and power quantity bids for matched GenCos. Outputs of an LSE's decision process for match making are shown in Figure 4.15 as components of data-flow K_l.

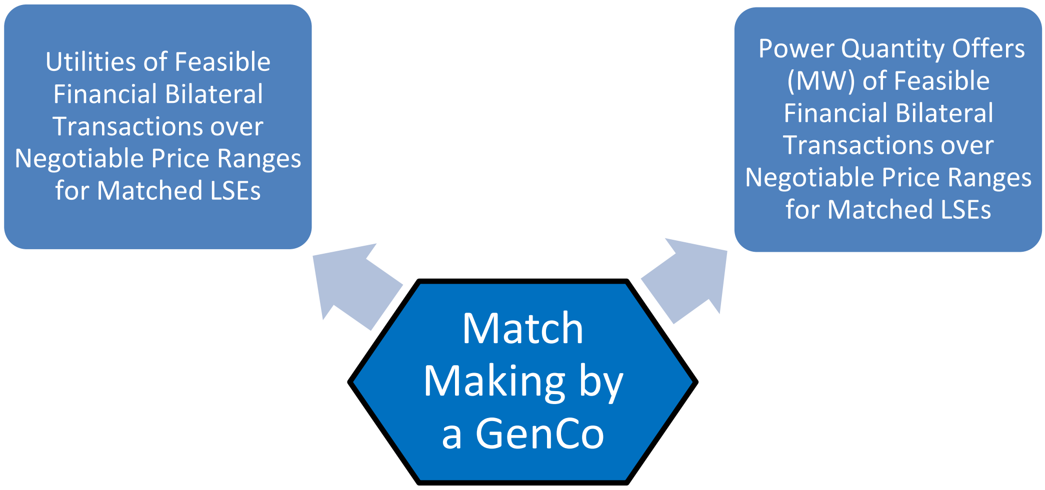

Figure 4.14 Components of Data Flow K_g: Outputs of Match Making by a GenCo

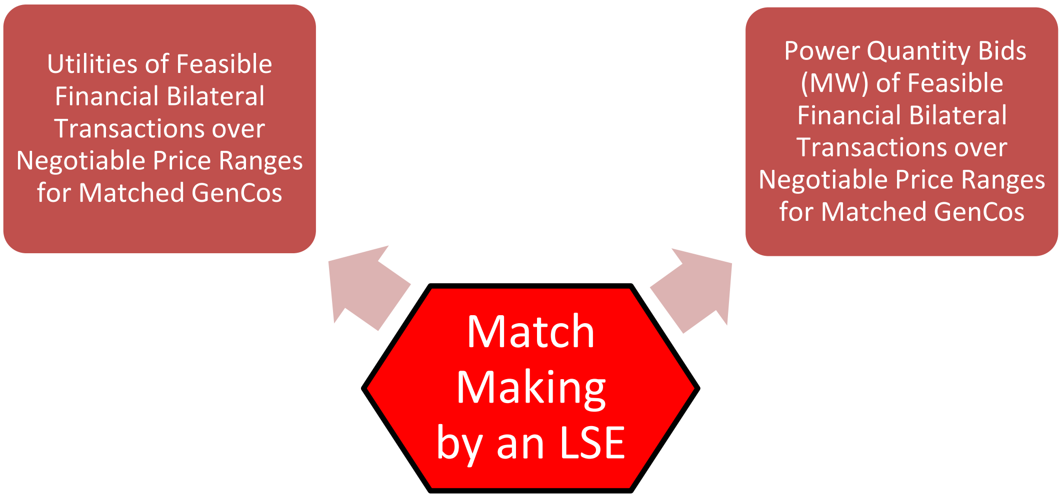

Figure 4.15 Components of Data Flow K_l: Outputs of Match Making by an LSE

GenCos and LSEs use the utility and power quantity results of match making to engage in bilateral negotiations. A successful annual bilateral negotiation leads to an year-long contract specifying agreed power quantity in MW and agreed energy price in $/MWh. In the absence of a centralized/organized bulletin-board or broker, each market participant needs to use some kind of a decentralized match making mechanism to conduct a direct-search for suitable partners. Even in a decentralized market, a uniform transaction protocol will avoid haphazard behaviour of participants and keep bilateral negotiation process in order.

4.2.2.2 Bilateral Negotiations for Financial Bilateral Transactions

After match making on the same day as announcement of FTR auction results, market participants use the next ten business days to engage in a multi-round (maximum five rounds) *bilateral negotiations* process, in FABS. Portfolio optimization based match making by a market participant develops private knowledge about utility of feasible Financial Bilateral Transactions and thus paves way for the participant to develop its own private strategy for *bilateral negotiations*. Power quantities and prices of Financial Bilateral Transactions are privately negotiated between each matched pair of GenCo and LSE. Successful *bilateral negotiations* lead to Financial Bilateral Transactions which specify agreed energy prices and quantities.

Two dynamic strategies are designed, one for a Generation Company and the other for a Load Serving Entity, for optimal *bilateral negotiations*. The novel dynamic strategies use utility based strategies and utilities of Financial Bilateral Transactions are determined by match making algorithms. A GenCo also has a novel adaptive strategy to support its dynamic strategy for *bilateral negotiations*. The adaptive strategy depends on Bayesian learning to estimate an LSE's maximum energy price bid, based on interactions during current multi-round *bilateral negotiations*.

Complete bilateral negotiation process and mathematical models of the negotiation strategies of a GenCo and an LSE are discussed in Chapter 8. Nevertheless, a graphical overview of inputs and outputs of bilateral negotiation process for market participants is presented next. Components of data-flow L_g (illustrated in Figure

4.16) are a GenCo's inputs to annual bilateral negotiation with a matched LSE. A GenCo needs utilities of its feasible bilateral transactions and power quantity offers for a matched LSE, over negotiable price range, to engage in the bilateral negotiation with the LSE. By comparison, an LSE needs power quantity bids and utilities of its feasible bilateral transactions with a matched GenCo for bilateral negotiation over negotiable price range. Figure 4.17 illustrates an LSE's inputs to annual bilateral negotiation as components of data-flow L_l. As a result of the decision making process of bilateral negotiations, GenCos and LSEs agree on prices and quantities of Financial Bilateral Transactions, if any, between specified source and sink nodes. Therefore outputs of the decision making, between a GenCo and an LSE, include agreed prices and quantities as well as source and sink nodes. Outputs of annual bilateral negotiation by a GenCo with an LSE are shown in Figure 4.18 as components of data-flow M_g. Figure 4.19 illustrates an LSE's outputs of annual bilateral negotiation with a GenCo as components of data-flow M_l.

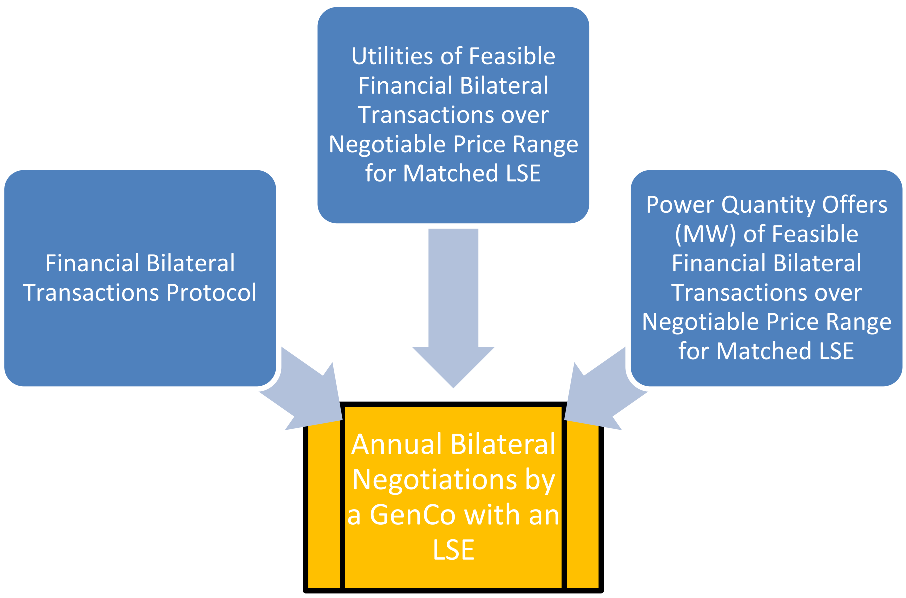

Figure 4.16 Components of Data Flow L_g: A GenCo's inputs to the decision process of annual bilateral negotiation with a Matched LSE

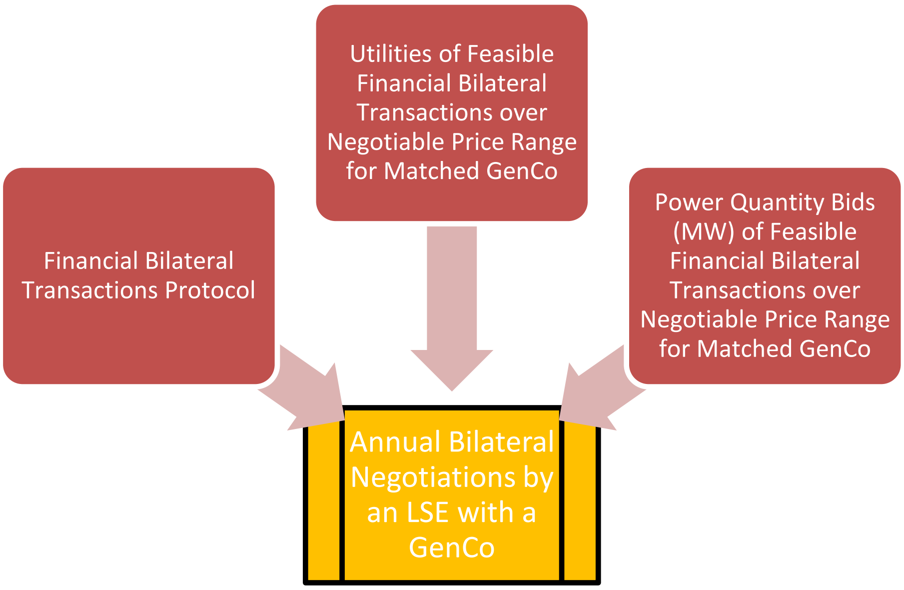

Figure 4.17 Components of Data Flow L_l: An LSE's inputs to the decision process of annual bilateral negotiation with a Matched GenCo

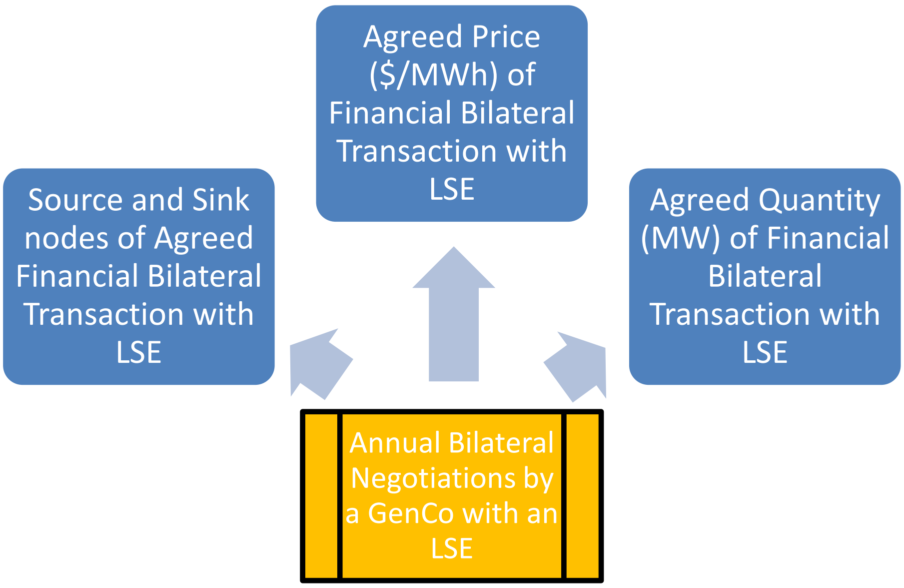

Figure 4.18 Components of Data Flow M_g: A GenCo's outputs of the decision process of annual bilateral negotiation with an LSE

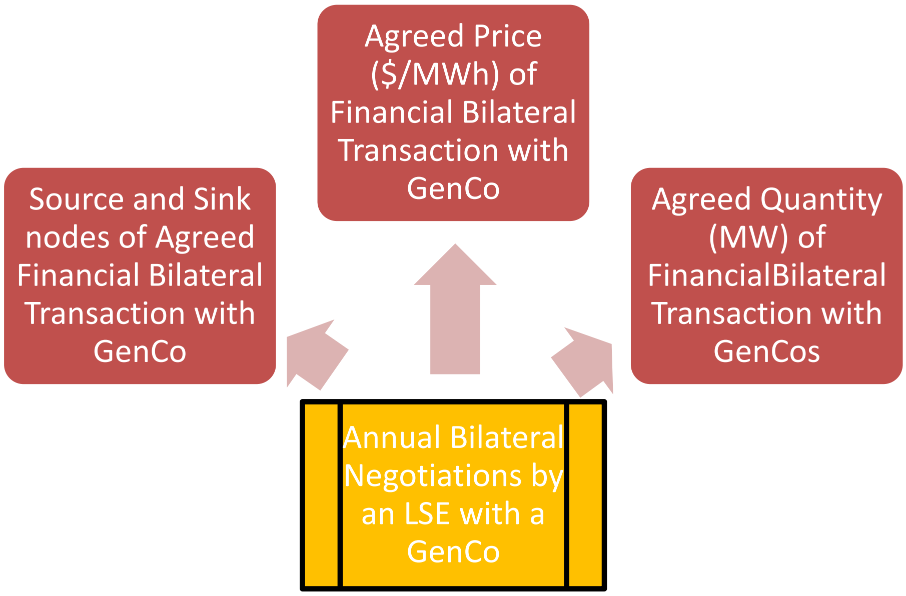

Figure 4.19 Components of Data Flow M_l: An LSE's outputs of the decision process of annual bilateral negotiation with a GenCo

4.3 Daily Sequence of Operations

Daily operations of energy market take place after all annual operations of FABS are complete. Mathematical details of daily sequence of operations are presented in Appendix C. The daily operations of energy market involve the eight data-flows, marked from N to S_g and S_l in Figure 4.1. Moreover, the figure shows that the daily operations include two decision processes: (i) day-ahead energy offers' optimization by each GenCo and (ii) day-ahead energy market clearing by ISO.

In FABS, organized day-ahead market is managed by ISO for energy trading between market participants. A day-ahead auction is conducted by ISO as a part of the overall day-ahead market. In the day-ahead auction, ISO collects *price-sensitive supply offers* of GenCos as well as *price-sensitive demand bids* and *price-inelastic load demands* of LSEs, for each hour of the next day. Price-inelastic load demands of LSEs must be fulfilled, irrespective of market prices, by independent system operator. Price-sensitive load demands are processed by ISO to determine which ones are most competitive and should be allowed as bid-based economic loads.

Similarly, price-sensitive supply offers are processed by ISO to determine which ones are most competitive and should be allowed as offer-based economic schedules.

In addition to the day-ahead auction, the day-ahead market can include *financial schedules* by market participants. ISO allows *financial schedules* so that sellers can supply and buyers can receive energy to fulfil their *Financial Bilateral Transactions*. A *financial schedule* is an option to participate in day-ahead market to transfer the financial responsibility for energy (not the physical flow of energy) between a buyer and a seller. Price-inelastic load demands and price-sensitive demand bids of LSEs remain fixed. However, GenCos can update their price-sensitive supply offers on daily basis.

4.3.1 Daily Optimization of Price-Sensitive Supply Offers by every GenCo

Graphical representation of inputs and outputs for daily optimization of GenCos' price-sensitive supply offers is described here. A GenCo's inputs to daily optimization of its price-sensitive supply offers are shown as components of data-flow N in Figure 4.20. The inputs include: (i) GenCo's calculated profit from its offers in previous day-ahead auction; (ii) fuel consumption based cost coefficients; (iii) generation capacity and (iv) agreed Financial Bilateral Transactions between source and sink nodes. Outputs of daily optimization of GenCos' price-sensitive supply offers are shown in Figure 4.21 as components of data-flow O.

LSEs and GenCos communicate their bids and offers to ISO for the day-ahead auction. In Figure 4.1, the communication of data from LSEs and GenCos is marked by data-flow P_l and data-flow P_g respectively. LSEs send hourly price-sensitive demand bids, hourly price-inelastic load demands and financial schedules to ISO, as illustrated in Figure 4.22 by components of data-flow P_l. The financial schedules indicate agreed Financial Bilateral Transactions between GenCos and LSEs. By contrast, GenCos only send financial schedules and price-sensitive energy offers to ISO, as shown in Figure 4.23 by components of data-flow P_g.

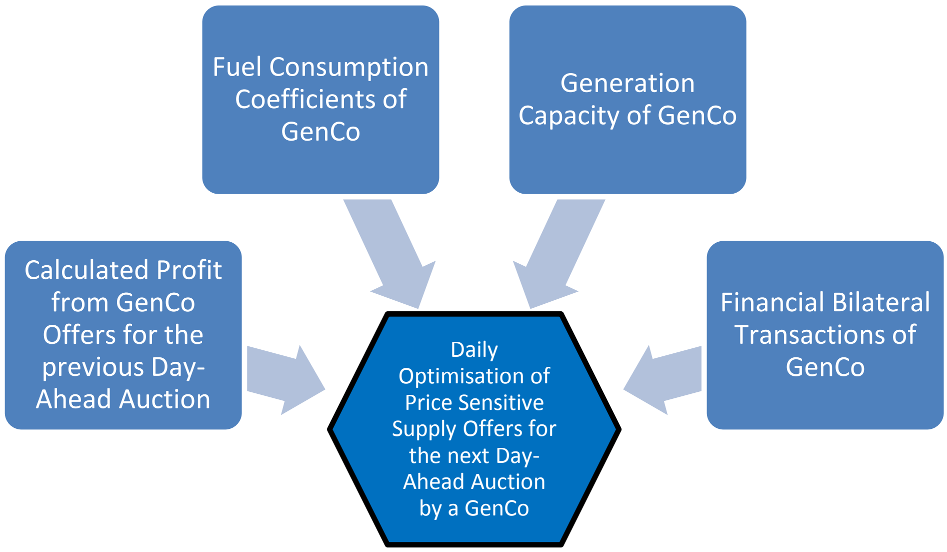

Figure 4.20 Components of Data Flow N: Inputs to each GenCo's decision process for optimal hourly price-sensitive supply offers

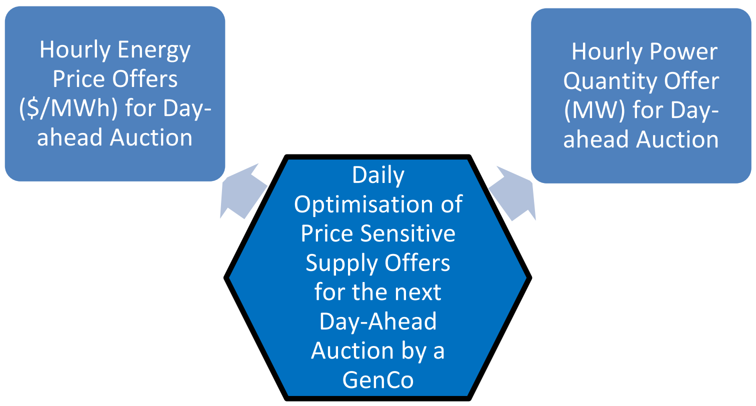

Figure 4.21 Components of Data Flow O: Outputs of each GenCo's decision process for optimal hourly price-sensitive supply offers

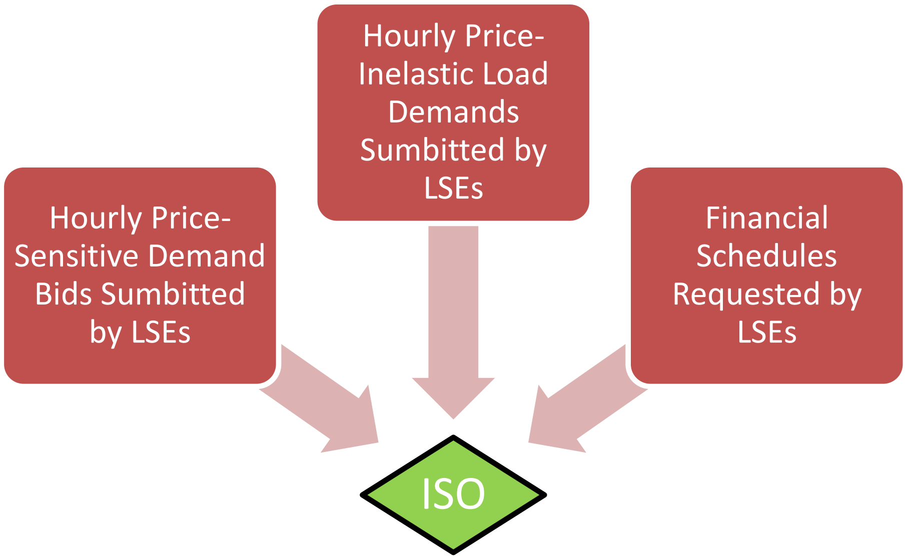

Figure 4.22 Components of Data Flow P_l: Communication of bids and other data for day-ahead energy market, from LSEs to ISO

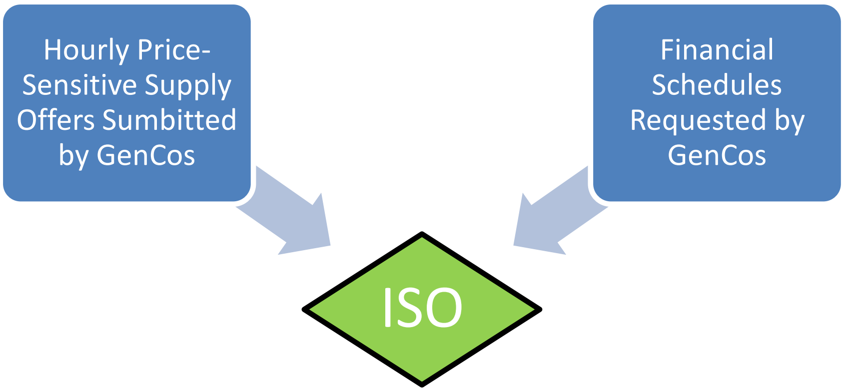

Figure 4.23 Components of Data Flow P_g: Communication of offers and other data for day-ahead energy market, from GenCos to ISO

4.3.2 Daily Optimal Clearing of Day-ahead Energy Market by ISO

GenCo and LSE agents in FABS have following options, or any combination of these options, to participate in the day-ahead energy market:

i. *Price-sensitive supply offers* of GenCos for selling energy in day-ahead auction at variable market prices through *offer-based economic schedules* determined by ISO;
ii. *Price-sensitive demand bids* of LSEs for buying energy in day-ahead auction at variable market prices through *bid-based economic loads* determined by ISO;
iii. *Price-inelastic load demands* of LSEs for buying energy in day-ahead auction irrespective of market prices;
iv. Financial schedules to fulfil Financial Bilateral Transactions between GenCos and LSEs.

In FABS, hourly profile of price-inelastic load demands remains fixed for each day of the simulation and ISO accepts all price-inelastic load demands of LSEs. Furthermore, ISO accepts all *financial schedules* because market participants limit their *Financial Bilateral Transactions* to simultaneous feasibility levels determined by ISO. In real world power systems, ISO may have to reduce accepted *financial schedules* for power system management under certain unforeseen circumstances. However, reductions in accepted *financial schedules* are not applicable in FABS because reliability and security constraints, including unforeseen transmission and generation failures, are not modelled.

ISO's daily inputs to the optimal clearing of day-ahead energy market are illustrated in Figure 4.24 as components of data-flow Q. The figure shows that ISO needs: (i) hourly price-sensitive supply offers; (ii) generator capacities; (iii) hourly price-sensitive demand bids; (iv) hourly price-inelastic load demands; (v) transmission capacities; (vi) financial schedules and (vii) source and sink nodes. During market clearing by DC Optimal Power Flow (DC-OPF), ISO ensures that: (i) all price-inelastic loads and financial schedules are met; (ii) most competitive price-sensitive supply offers and demand bids are accepted and (iii) no transmission or generation capacity is violated. As a result of optimal market clearing, ISO finds: (i) offer-based economic schedules; (ii) bid-based economic loads; (iii) LMPs at all nodes and power flow through all transmission lines; (iv) allowed price-inelastic load demands and (v) allowed financial schedules. The ISO's outputs of day-ahead market clearing are shown in Figure 4.25 as components of data-flow R.

Every day ISO communicates results of market clearing to LSEs and GenCos, as indicated in Figure 4.1 by data-flow S_l and data-flow S_g respectively. Figure 4.26 shows four components of data-flow S_l from ISO to LSEs: (i) bid-based economic loads, (ii) allowed price-inelastic load demand, (iii) LMPs at all nodes and (iv) allowed financial schedules. Data-flow S_g from ISO to GenCos has three components (illustrated in Figure 4.27): (i) offer-based economic schedules, (ii) LMPs at all nodes and (iii) allowed financial schedules.

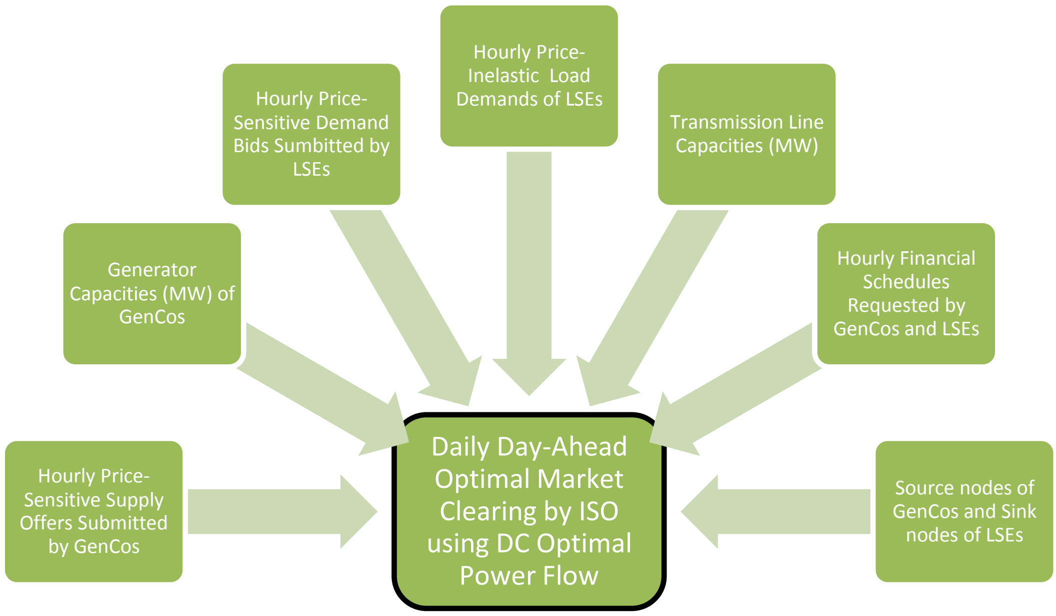

Figure 4.24 Components of Data Flow Q: Inputs to ISO's decision process for optimal clearing of day-ahead energy market

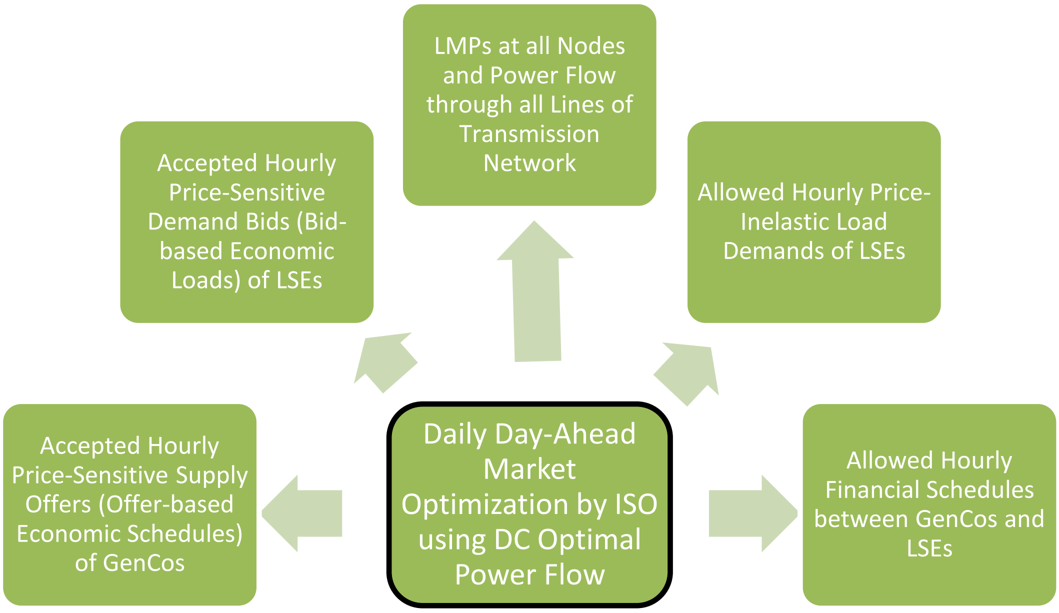

Figure 4.25 Components of Data Flow R: Outputs of ISO's decision process for clearing day-ahead energy market

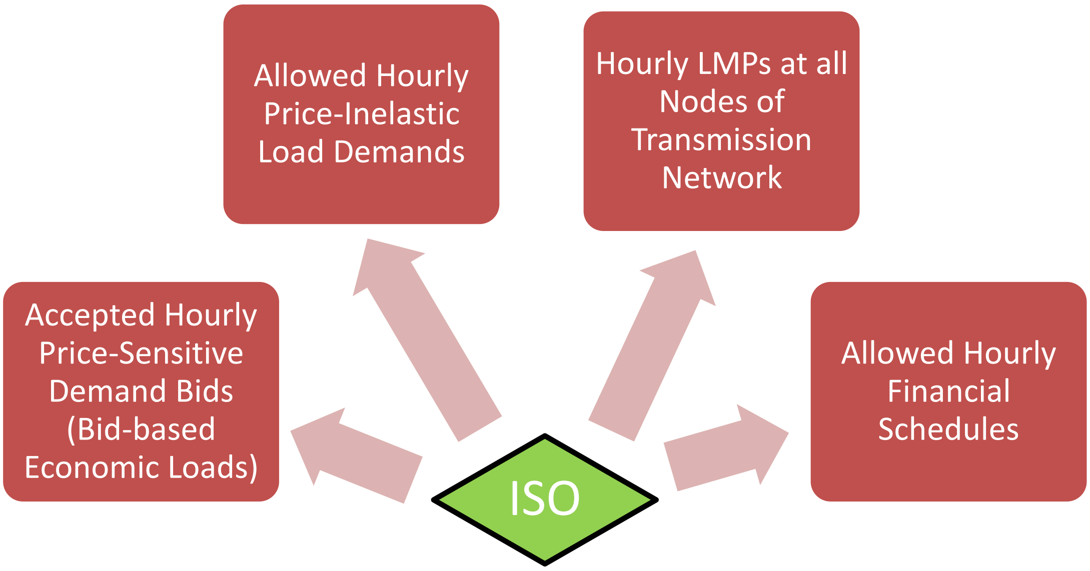

Figure 4.26 Components of Data Flow S_l: Communication of day-ahead energy market clearing results from ISO to LSEs

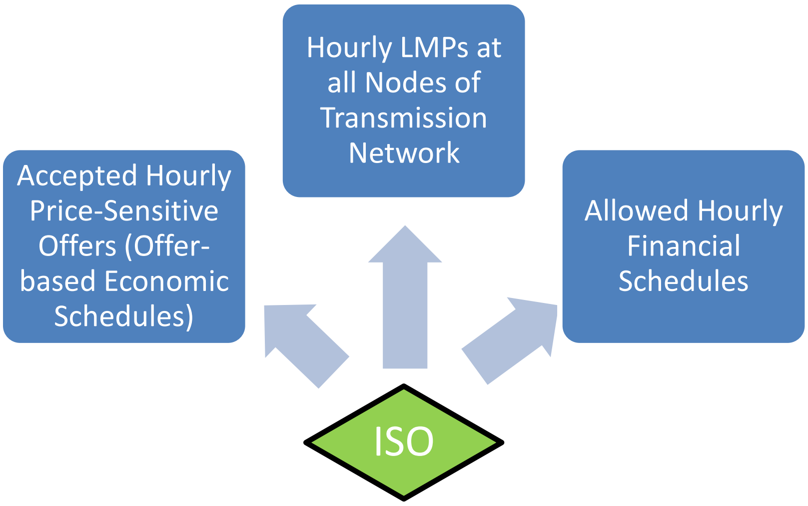

Figure 4.27 Components of Data Flow S_g: Communication of day-ahead energy market clearing results from ISO to GenCos

4.4 Monthly Sequence of Operations

Monthly settlement operations occur at the end of each month - thirty days of daily operations in FABS. These operations facilitate financial settlement of traded energy, transmission congestion, as well as FTRs and ARRs between ISO and market participants. Mathematical details of monthly sequence of operations are available in Appendix C. The monthly settlement operations involve the eight data-flows, marked from T to X_g and X_l in Figure 4.1. The figure also shows that monthly market settlements and monthly bilateral settlements are the two types of decision processes that are included in the monthly operations.

4.4.1 Monthly Market Settlements between ISO and Market Participants

Monthly market settlements allow market participants to make and receive payments for energy traded through the day-ahead auction. In addition, the settlements include payments for transmission congestion costs, Financial Transmission Rights and

Auction Revenue Rights. ISO has day-ahead energy market data of every hour in the previous month including LMPs, loads, economic schedules and financial schedules. Furthermore, ISO knows allocated ARRs, awarded FTR quantities and prices as well as source and sink nodes. As illustrated in Figure 4.28 by components of data-flow T, the aforementioned data serves as ISO's inputs to decision process for market settlements. For market settlements of previous month, ISO calculates: (i) payments of energy costs by LSEs to ISO; (ii) payments of transmission congestion costs by LSEs to ISO; (iii) payments of FTR credits by ISO to LSEs; (iv) payments of ARR credits by ISO to LSEs and (v) payments of energy costs by ISO to GenCos. These five outputs of ISO's decision process for market settlements are shown in Figure 4.29 as components of data-flow U.

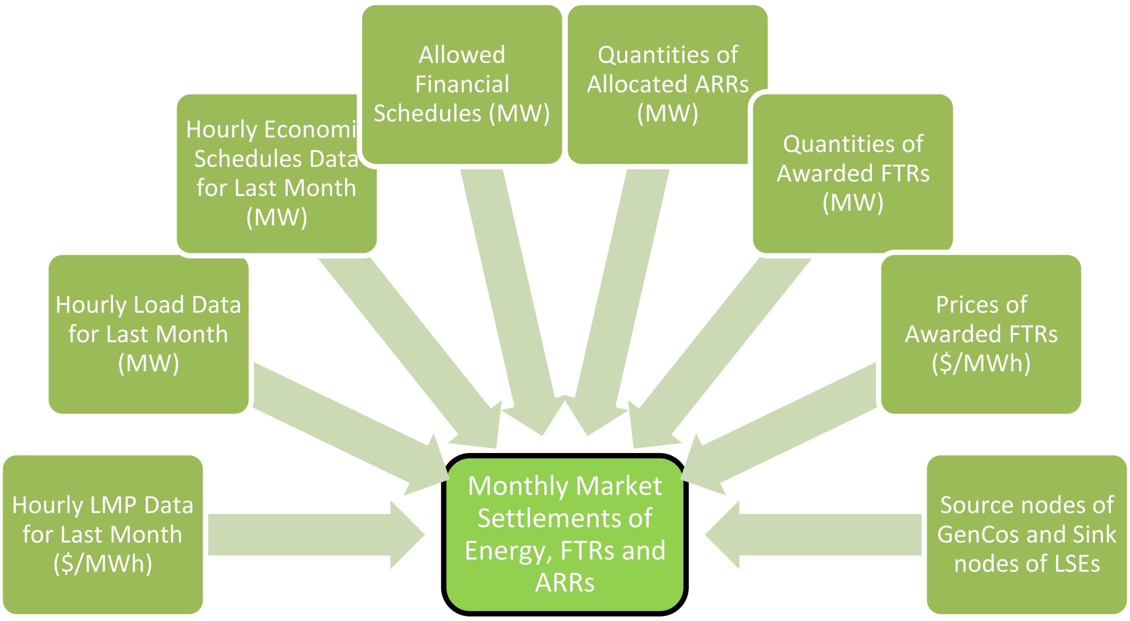

Figure 4.28 Components of Data Flow T: Inputs to ISO's decision process for monthly market settlements of energy, FTRs and ARRs

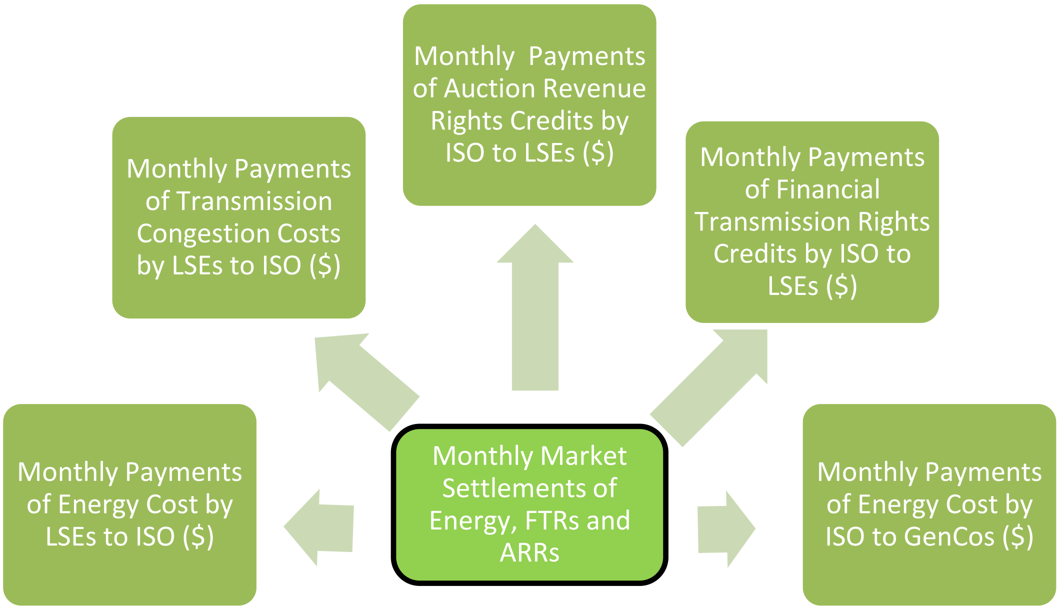

Figure 4.29 Components of Data Flow U: Outputs of ISO's decision process for monthly market settlements of energy, FTRs and ARRs

Each month, ISO communicates its calculations for market settlements of energy and transmission costs to every LSE and GenCo by data-flow V_l and data-flow V_g respectively. Figure 4.30 shows that data-flow V_l has four components: (i) payments of energy costs (for energy purchased in day-ahead auction) by the LSE to ISO; (ii) payments of transmission congestion costs (including transmission congestion costs caused by energy traded through financial schedules) by the LSE to ISO; (iii) payments of FTR credits by ISO to the LSE and (iv) payments of ARR credits by ISO to the LSE. Note that LSEs have to pay for transmission congestion costs of financial schedules to ISO. The transmission congestion cost of a financial schedule depends on difference between LMPs at sink and source nodes and power quantity. If an LSE holds an FTR equal to its corresponding financial schedule then the transmission congestion cost can be fully hedged. If, however, LSE has less FTR than the financial schedule then the transmission congestion cost are only partially hedged.

By contrast with an LSE, data-flow V_g in Figure 4.31 shows that ISO only sends calculated payments for energy sold by a GenCo in day-ahead auction because GenCos are not responsible for any transmission related costs in FABS.

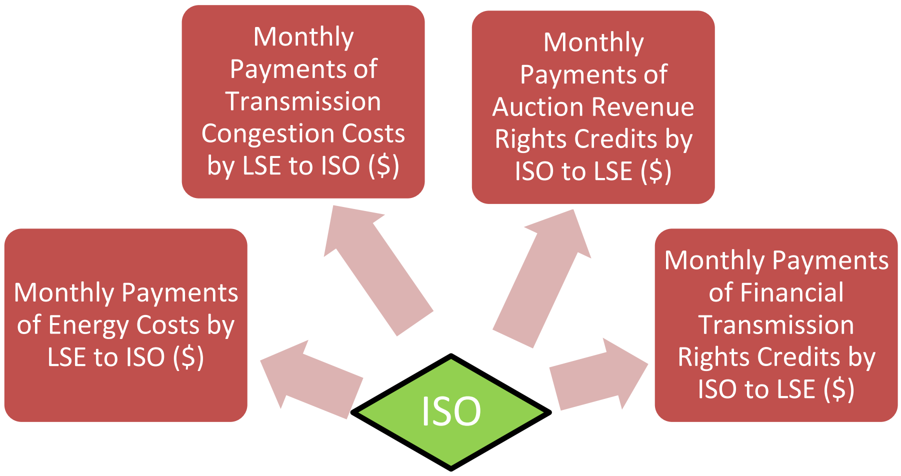

Figure 4.30 Components of Data Flow V_l: Communication of monthly market settlements' results from ISO to each LSE

Figure 4.31 Components of Data Flow V_g: Communication of monthly market settlements' results from ISO to each GenCo

4.4.2 Monthly Bilateral Settlements between Market Participants

Monthly bilateral settlements allow market participants to make and receive payments for energy traded through financial schedules. ISO allows LSEs to directly pay GenCos for energy quantities traded by financial schedules. Consequently, energy component of financial schedules is bilaterally settled out of day-ahead market. Graphical representation for inputs and outputs of bilateral settlements process is described next. Components of data-flow $\mathbf{W_g}$ (illustrated in Figure 4.32) are a GenCo's inputs to the bilateral settlement process with an LSE. A GenCo needs agreed power quantity and energy price with an LSE to calculate monthly payment for energy. Similarly, an LSE calculates its monthly payment to a GenCo on the basis of agreed power quantity and energy price with the GenCo. Figure 4.33 illustrates an LSE's inputs to monthly bilateral settlement with a GenCo as components of data-flow $\mathbf{W_l}$.

Output of monthly bilateral settlement between a GenCo and an LSE is the same for both entities. They determine monthly payment for energy by LSE to GenCo as shown in Figure 4.34 and Figure 4.35 by data-flow $\mathbf{X_g}$ and data-flow $\mathbf{L_l}$ respectively.

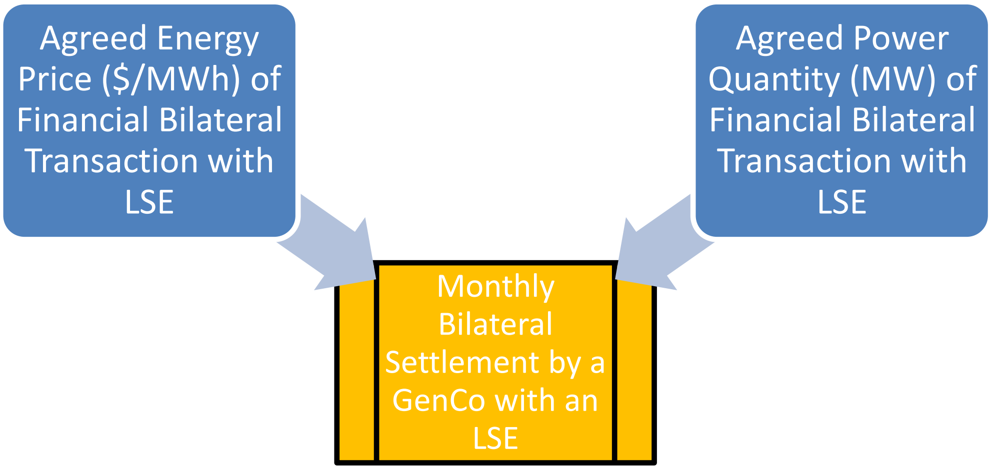

Figure 4.32 Components of Data Flow W_g: A GenCo's inputs to the decision process of monthly bilateral settlement with an LSE

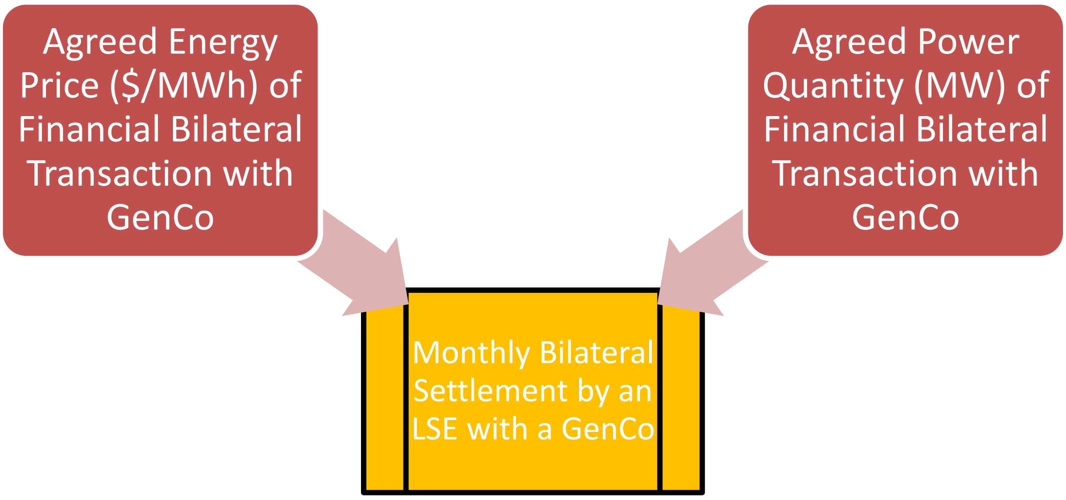

Figure 4.33 Components of Data Flow W_l: An LSE's inputs to the decision process of monthly bilateral settlement with a GenCo

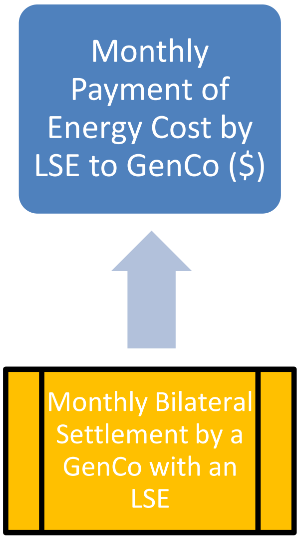

Figure 4.34 Components of Data Flow X_g: A GenCo's outputs of the decision process of monthly bilateral settlement with an LSE

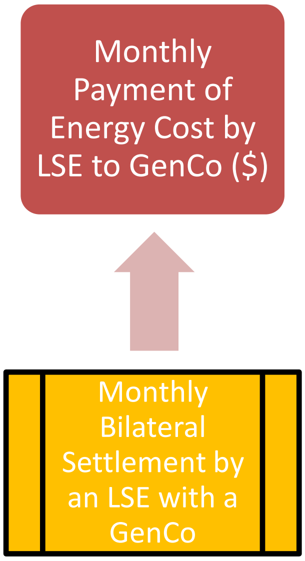

Figure 4.35 Components of Data Flow X_l: An LSE's outputs of the decision process of monthly bilateral settlement with a GenCo

4.5 Conclusions

This chapter has outlined a brief description of electricity market model used in FABS. ARR allocation, FTR auction and decision making for Financial Bilateral Transactions are annual operations that occur at the beginning of a simulation year. Thereafter, daily optimization of offers for day-ahead auction and clearing of day-ahead auction take place before start of actual delivery day. Settlements of organized and bilateral electricity trades are monthly operations that are carried out at the end of each month.

Decision processes and data-flows are crucial components of the simulated market operations in FABS. A flowchart illustrates sequence of decision making processes of market participants and ISO. The flowchart also indicates data-flows that carry inputs and outputs of the decision processes as well as data-flows for communication between the market participants. Graphical representations of components in each data-flow are used to discuss the simulated market operations in FABS.

4.6 References

[1] H. Markowitz, "Portfolio Selection," *Journal of Finance*, vol. 8, pp. 77-91, 1952.

5 Annual Auction Revenue Rights Allocation and Annual Financial Transmission Rights Auction

5.1 Introduction

In North America, a number of electricity markets have incorporated auctions of Financial Transmission Rights (FTRs) and some have also introduced allocations of Auction Revenue Rights (ARRs) [1]. An FTR is a financial hedging instrument to manage the risk of congestion cost in day-ahead energy markets. An ARR is another financial hedging instrument to manage the uncertain cost of obtaining FTRs, as described after following discussion on FTRs. Independent system operator (ISO) is a non-profit public body that conducts FTR auctions for profit-seeking market participants, mainly Load Serving Entities (LSEs). Since ISO is a non-profit public body, it is bound to distribute transmission congestion revenue, collected from LSEs as their congestion charges, among LSEs. By conducting an annual FTR auction, ISO facilitates distribution of transmission congestion revenue to LSEs to offset their congestion charges. An optimal FTR auction clearing facilitates a fair payback of ISO's transmission congestion revenue to LSEs that receive transmission congestion credits for cleared FTR quantities. The payback is fair because it depends on FTRs obtained through a competitive auction clearing process that facilitates a fair competition among participants.

An FTR specifies power quantity that will have Financial Transmission Right from a source node to a sink node. An FTR is a financial instrument that does not entitle its holder to a physical right for power delivery. Financial Transmission Rights can be obligation FTRs or option FTRs. An obligation FTR holder can be either entitled to a payment for congestion credits or liable to a payment of congestion charges. On the other hand, an option FTR holder may be entitled to congestion credits but not liable to congestion charges. Difference between LMPs at the sink and source nodes of an FTR determines whether FTR holder gets credits or incurs charges. If LMP at the sink node is higher than LMP at the source node then obligation/option FTR holder gets congestion credits. Otherwise, obligation FTR holder incurs congestion charges but option FTR holder avoids any congestion charges. An FTR credit payment for one hour equals the product of the FTR quantity (MW) and the difference in LMPs ($/MWh) at the agreed source and sink points [2], [3].

In practical markets, like MISO, annual FTR auction is a multi-round process. Multi-round FTR auctions allow market participants to adjust their FTRs according to their requirements. If they acquire some unwanted FTRs in initial round they can sell those FTRs in successive rounds. Furthermore, if they fail to fulfil their FTR requirements in the initial round then they can buy more FTRs in later rounds. In addition to being a multi-round auction, annual FTR auction is a multi-period market that caters for periodic seasonal and daily variations in load demands and energy prices. In each round, practical markets hold separate annual auctions for four seasons of a year. Furthermore, auction for each season can be multi-product auction consisting of both obligation and option FTRs.

An ARR is another financial hedging instrument to manage the uncertain cost of obtaining FTRs. ISO conducts ARR allocations for market participants, like LSEs, that are liable to congestion charges and need to acquire FTRs to hedge against the congestion charges. As will be explained in 5.3, ISO calculates LSEs' ARR allocations on the basis of (i) LSEs' ratios of historical peak system load, (ii) maximum available capacities of GenCos, (iii) FTR requirements of LSEs, (iv) maximum capacities of transmission lines and (v) base load requirements of LSEs. ISO must distribute FTR auction revenue, collected from LSEs as their FTR acquisition costs, among LSEs because it is a non-profit organization. Annual ARR allocation, facilitates distribution of FTR auction revenue among FTR bidders to offset their annual FTR acquisition costs. An ARR holder is entitled to a payment out of ISO's FTR auction revenue. ISO's payment to an ARR holder equals the product of its ARR quantity (MW) and FTR price ($/MW) between the sink and source nodes of the ARR. It is crucial to realize that market participants do not have to hold FTRs or ARRs in order to schedule Financial Bilateral Transaction. Nor they are forced to schedule Financial Bilateral Transaction just because of owning FTRs or ARRs.

Previous work on simulation of FTR bidding and auction is presented in [4], [5] and [6], as discussed in detail in Section 3.3.3. Agent-based simulation of FTR bidding and auctions presented in [4] and [5], provides detailed modelling of simulated FTR markets that determine a market clearing price. Multi-round, multi-period and multi-product auction models are used in [4] and [5]. These models assume that FTR bid quantities are fixed at specified levels, while initial values of FTR bid prices are set according to the difference between expectations of LMPs at source and sink of FTR. An annual FTR bid price is the difference between expectations of LMPs at source and sink of the FTR multiplied by the number of hours in a year. Both papers present a number of case studies for *stationary* conditions. Annual FTR auction is only conducted for one year in [4]. However, in [5], simulation of annual FTR auction is repeated under *stationary* conditions and a naïve reinforcement learning method is used to adjust, before each iteration, FTR bid prices by simple decision rules.

In [6], ISO determines maximum available FTR quantities and FTR bidders choose those quantities as their bid quantities. Moreover, a risk-constrained bidding strategy and the difference between expectation of LMPs at source and sink of an FTR are used to determine the FTR bid price. It is assumed that an FTR bidder has incomplete information models of its opponents but all opponents' bidding strategies remain *stationary*. The bidder uses Bayesian Nash equilibrium to solve the incomplete information game. Contrary to practical electricity market scenario, the game theoretic approach assumes that a bidder is optimizing its bids in a *stationary* environment. However, as shown in this chapter, an appropriate risk analysis method can be developed and deployed in an agent-based environment to incorporate *dynamic* bidding strategies of all FTR bidding agents.

Since this thesis focuses on optimal operating strategies of market participants, each LSE's optimization of its bids for FTRs is extensively modelled in FABS. As a reminder FABS stands for "Financial transmission instruments, energy Auction and Bilateral transaction Simulator for wholesale electricity markets". However, only simplified models are used for ARR allocation and FTR auction by ISO because of their secondary importance in FABS. For simplicity, ISO only conducts a single-round auction for obligation FTRs and only awards FTRs as obligations because FTR obligations are mainly used for hedging congestion costs in practical LMP markets [7]. Since seasonal variations are not modelled in FABS, it does not need a multi-period FTR auction model. Among all market participants in FABS, only LSEs are allowed to bid in the FTR auction because only they are responsible for payment of congestion charges. The auction is intended for base load requirements of LSEs and speculative bidding is not allowed. Simulation of annual FTR auction follows simulation of annual ARR allocation.

The rest of this chapter is organized as follows. Formulae for statistical analysis of past LMPs are provided in Section 5.2. Mathematical details of ARR allocation, FTR bid optimization and FTR auction are presented in Sections 5.3, 5.4 and 5.5 respectively. Case studies and results are presented in Section 5.7 and Section 5.8 respectively, whereas Section 5.8 concludes this chapter.

5.2 Statistical Analysis of Past LMPs

ISO and different market participants need statistical analysis of past LMPs during their decision making processes related to aspects of financial transmission instruments and Financial Bilateral Transactions. For instance, ISO needs to determine overall expectation of LMPs, while each LSE needs to know overall expectation, variance and covariance of LMPs for decision making related to financial transmission instruments, as described in this Chapter. ISO uses overall expectation of LMPs for allocation of Auction Revenue Rights. LSEs use overall expectation, variance and covariance of LMPs for decisions of investment in Financial Transmission Rights to hedge against transmission congestion costs.

Moreover, as will be discussed in Chapter 6, each GenCo and LSE needs to do similar statistical analysis of LMPs from the previous year before carrying out portfolio optimization for the following year. Portfolio optimization involves decisions of investment in Financial Bilateral Transactions to hedge against uncertain revenues/costs of electricity trading in day-ahead auction.

Calculations of overall expectation $E(\lambda_i)$, variance $\sigma^2(\lambda_i)$, covariance $\sigma(\lambda_i, \lambda_j)$ and standard deviation $\sigma(\lambda_i)$ of LMPs are discussed as follows. The calculations require LMP data for a historical period, consisting of a total of *Z* trading intervals in the past. A historical period may be a month, a year or any other length of time. Note that formulae in this section use *i* and *j* for indices of nodes and *z* is an index for a trading interval.

Investment decisions for FTRs or bilateral transactions need careful evaluation of risk-return trade-off. An investment decision for FTRs or bilateral transactions is made for a specified period. The decision period can be a month, a year or any other length of time. An investment's rate of return, in short return, is its benefit-to-cost ratio that is a measure of its financial performance. Benefit of an investment is determined by the difference between its revenue and cost. In this thesis, revenue, cost and return refer to a specific investment for a specified decision period. Thus, return is defined as,

$$Return = \frac{Revenue - Cost}{Cost} = \frac{Revenue}{Cost} - 1 \tag{5.1}$$

If, instead of revenue or cost, only expected revenue or expected cost is known then only expected return can be determined. For each investment, a market participant needs to evaluate its expected return. These expected returns count towards the "return" aspect in the risk-return trade-off and depend on expectations of LMPs. Using LMP data of a historical period consisting of *Z* trading intervals, expectation of LMP at node *i* is given by,

$$E(\lambda_i) = \frac{\sum_{z=1}^{Z} \lambda_{i,z}}{Z} \tag{5.2}$$

Compared to concise definition of return by equation (5.1), risk is a relatively abstract concept. The concept of risk represents a decision maker's exposure to danger because of uncertainty [8]. Consequently, both exposure and uncertainty are essential components of risk. However, a practical decision maker only has its own perceptions of exposure and uncertainty that may not be true reflections of actual exposure and uncertainty. Therefore, for the "risk" aspect of the risk-return trade-off, the decision maker needs to evaluate some practical attributes of its perceived risk [9]. Following Markowitz approach [10], this thesis specifies variance of return as a risk metric of the perceived risk. The variance of return depends on variances of returns of investments as well as covariances between returns of investments.

The decision maker has to evaluate variances of returns for its investments. The variances of returns depend on variances of LMPs. Using LMP data of a historical period consisting of Z trading intervals, variance of LMP at node *i* is calculated as,

$$\sigma^2(\lambda_i) = \frac{\sum_{z=1}^{Z}\left(\lambda_{i,z}\right)^2 - \left(\sum_{z=1}^{Z}\lambda_{i,z}\right)^2 \Big/ Z}{Z-1} \tag{5.3}$$

The decision maker also needs to evaluate covariances between returns of FTR investments and covariances between returns of bilateral transactions. Covariances between returns for investments depend on covariances of LMPs. Using LMP data of a historical period consisting of *Z* trading intervals, covariance between LMPs at nodes *i* and *j*, is given by,

$$\sigma(\lambda_i, \lambda_j) = \frac{\sum_{z=1}^{Z}\left(\lambda_{i,z} - \mu_i\right)\left(\lambda_{j,z} - \mu_j\right)}{Z-1} \tag{5.4}$$

Standard deviation of an LMP is a measure of its spread around the expected value. As will be discussed in Chapter 7, each GenCo and LSE needs to know standard deviations of LMPs to determine a mutually acceptable range in which energy prices can be quoted during bilateral negotiation. Using LMP data of a historical period consisting of *Z* trading intervals, standard deviation of LMP at node *i*, is calculated as,

$$\sigma(\lambda_i) = \sqrt{\frac{\sum_{z=1}^{Z}\left(\lambda_{i,z}\right)^2 - \left(\sum_{z=1}^{Z}\lambda_{i,z}\right)^2 \Big/ Z}{Z-1}} \tag{5.5}$$

5.3 Auction Revenue Rights Allocation

Unlike FTRs that are awarded after a competitive auction, annual ARRs are allocated on the basis of (i) LSEs' ratios of historical peak system load, (ii) maximum available capacities of GenCos, (iii) FTR requirements of LSEs, (iv) maximum capacities of transmission lines and (v) base load requirements of LSEs. A description of the overall allocation process is presented as follows.

Each LSE needs ARRs to hedge acquisition costs of FTRs from GenCos' nodes to its local node. ISO is aware that maximum load flow from a source node to all sink nodes cannot exceed total generation capacity at the source node. Therefore, total FTR quantity, and hence total ARR quantity, from a source node to all sink nodes cannot exceed total generation capacity at the source node. ISO tentatively divides the total ARR quantity, from a source node to all sink nodes, among all LSEs proportionate to their ratios of historical peak system load, as discussed in Section 5.3.1.

LSEs do not need FTRs for bilateral transactions with GenCo at their local node because local bilateral transactions do not use transmission network. Therefore, ISO does not allocate an ARR to an LSE for a GenCo located at its local node. In addition, ISO does not allocate ARR between a source node and a sink node when it knows that LSE does not need corresponding FTR, for reasons explained in Section 5.3.2.

Since ISO is responsible for overall operation of power system, it has to ensure that transmission system can simultaneously support all allocated ARRs. ISO tests simultaneous feasibility of ARRs by a load flow analysis and if ARR flows exceed transmission line capacities then proportionately reduces the ARRs, as described in Section 5.3.3.

In FABS, ISO allocates ARRs to LSEs that use them as hedge against their FTR acquisition costs. ISO auctions FTRs so that LSEs can hedge against transmission congestion costs of meeting their base load requirements. Therefore, if sum of an LSE's feasible ARRs exceeds its base load requirement then ISO proportionately reduces the ARRs to eliminate the excess ARRs, as explained in Section 5.3.4.

5.3.1 Initial Auction Revenue Rights based on Load Ratios and Generation Capacities

Auction revenue rights of LSEs depend on their ratio of contribution to historical peak system load. Historical peak system load is the peak system load that occurred during the historical period under consideration. ISO calculates load ratio of LSE connected at sink node *k*, LR_k, by taking into account LSE's load at the time of historical peak system load, Ld_k^{Pk}, as well as the historical peak system load, $\sum_{k=1}^{K} Ld_k^{Pk}$, i.e.,

$$LR_k = \frac{Ld_k^{Pk}}{\sum_{k=1}^{K} Ld_k^{Pk}} \tag{5.6}$$

In general, power flows from a GenCo connected at a source node to an LSE connected at a sink node. Therefore, first letter of source, *s*, is used as index of a source node and last letter of sink, *k*, is used as an index of a sink node. Initial ARR between each source node *s* with a total generation capacity GC_s^{total} and sink node *k* with load ratio LR_k, is denoted by $ARR_{sk}^{initial,quantity}$, and calculated as,

$$ARR_{sk}^{initial,quantity} = GC_s^{total} \times LR_k \tag{5.7}$$

As shown in (5.7), initial ARRs between source node *s* and sink node *k* are assigned on the basis of load ratio of LSE at node *k* and total available generation capacity of GenCo(s) at node *s* [11]. However, as their name suggests, initial ARRs are tentative and need to be scrutinized by ISO before ARR allocation to LSEs. Initial ARRs have to pass through a number of checks and adjustments. Reasons and details of the checks and adjustments are explained in following steps of the overall ARR allocation process.

5.3.2 Positive Auction Revenue Rights based on Financial Transmission Rights Requirements of Load Serving Entities

Since ARRs are allocated to hedge cost of FTR acquisition, ISO must check that it only allocates ARRs to those source-sink combinations for which LSEs actually need FTRs. For instance, source and sink nodes are the same in case of local bilateral transactions that do not use transmission network. Consequently, LSEs do not need FTRs for local bilateral transactions and hence ISO should not allocate ARRs for source-sink combinations corresponding to local bilateral transactions. As another example, LSEs do not need FTRs if expectation of LMP at their local node is less than expectation of LMP at a GenCo node, due to reasons explained in following paragraphs. If LSEs do not need FTRs for a source-sink combination then ISO should not allocate ARRs for the source-sink combination. In FABS, ISO avoids these unnecessary ARR allocations, as explained next.

Based on data of previous LMPs in the historical period, ISO forecasts average expectation of LMPs by (5.2). The difference between overall expectations of LMPs at each source node *s* and sink node *k* , $\Delta\lambda_{sk}^{\exp}$, is given by,

$$\Delta\lambda_{sk}^{\exp} = E(\lambda_k) - E(\lambda_s) \qquad (5.8)$$

In case overall expectation of LMP at source node *s* is lower than overall expectation of LMP at sink node *k*, the difference in overall expectation of LMPs has a positive value, $\Delta\lambda_{sk}^{\exp} > 0$. Otherwise, the difference in expectations of LMPs may have a zero or a negative value, $\Delta\lambda_{sk}^{\exp} \le 0$. Effects of values of $\Delta\lambda_{sk}^{\exp}$ on auctioned FTRs and allocated ARRs are summarized in Table 5.1 and described as follows.

Table 5.1 Effects of Expectation of Difference in Locational Marginal Prices between Source and Sink Nodes

Value of $\Delta\lambda_{sk}^{\exp}$	**Expected Effect on Obligation FTR**	**Effect on** $ARR_{sk}^{positive,quantity}$
$\Delta\lambda_{sk}^{\exp} > 0$	Expected to get FTR credits	$ARR_{sk}^{positive,quantity} = ARR_{sk}^{initial,quantity}$
$\Delta\lambda_{sk}^{\exp} < 0$	Expected to incur FTR charges	$ARR_{sk}^{positive,quantity} = 0.$
$\Delta\lambda_{sk}^{\exp} = 0$	Neither expected to incur FTR charges nor get FTR credits	$ARR_{sk}^{positive,quantity} = 0.$

If $\Delta\lambda_{sk}^{\exp}$ corresponding to an obligation FTR is a positive value, then FTR holder is expected to get credits. However, if $\Delta\lambda_{sk}^{\exp}$ corresponding to an obligation FTR is a negative value, then FTR holder is expected to incur charges. In case $\Delta\lambda_{sk}^{\exp}$ corresponding to an obligation FTR has a zero value, FTR holder is neither expected to incur charges nor get credits. Market participants only bid for an obligation FTR if its corresponding $\Delta\lambda_{sk}^{\exp}$ has a positive value because they acquire obligation FTRs in expectation of earning credits instead of incurring charges.

Note that even for some positive values of expected LMP differences, $\Delta\lambda_{sk}^{\exp}$, actual LMP differences, $\Delta\lambda_{sk}^{act}$, may fall below zero due to extreme conditions of dynamic market during some periods in the day. For those periods, a market participant holding obligation FTR between source node *s* and sink node *k* will be liable to pay FTR charges to ISO, instead of receiving an FTR credit from ISO.

Since ARRs are allocated to hedge cost of FTR acquisition, ISO only allocates an ARR when source and sink nodes are different and corresponding $\Delta\lambda_{sk}^{\exp}$ is a positive quantity. Consequently, positive ARRs between each source node *s* and sink node *k*, $ARR_{sk}^{positive,\,quantity}$, are determined by,

$$ARR_{sk}^{positive,quantity} = \begin{cases} ARR_{sk}^{initial,quantity} & , \quad \Delta\lambda_{sk}^{\exp} > 0 \\ 0 & , \quad \Delta\lambda_{sk}^{\exp} \leq 0 \end{cases} \tag{5.9}$$

5.3.3 Load Flow Analysis of Positive Auction Revenue Rights as a Simultaneous Feasibility Test

Allocated ARRs must be simultaneously feasible to ensure that transmission system can support the allocated set of ARRs [11]. This is known as Simultaneous Feasibility Test or criterion. After determining positive ARRs, ISO conducts a load flow analysis for all positive ARRs, $ARR_{sk}^{positive,quantity}$, to see if they are simultaneously feasible. Power flows through all transmission lines, resulting from the positive ARRs, are calculated using power transfer distribution factors. If power flows through transmission lines are less than transmission line capacities then positive ARRs satisfy simultaneous feasibility criterion. However, if power flow through any transmission line exceeds its capacity then positive ARRs are not simultaneously feasible.

If power flows due to positive ARRs exceed capacities of more than one transmission line then it is necessary to identify transmission line *oe* (origin node *o* and end node *e*) that experiences highest percentage of overflow, Fl_{oe}^{over}, above its capacity, $Fl_{oe}^{capacity}$. Transmission line experiencing highest over flow indicates greatest violation of network flow constraints. It also indicates the violation that needs to be addressed to satisfy simultaneous feasibility criterion.

Those positive ARRs that cause network flow violations are proportionately reduced by ISO to satisfy transmission line constraints. For proportionate reduction, ISO calculates a power flow reduction factor, $PFRF_{ISO}$, by,

$$PFRF_{ISO} = \frac{Fl_{oe}^{capacity}}{Fl_{oe}^{over}} \tag{5.10}$$

Proportionate reduction of positive ARRs, $ARR_{sk}^{positive,quantity}$, according to power flow reduction factor, $PFRF_{ISO}$, leads to calculation of feasible ARRs between each source node *s* and sink node *k*, $ARR_{sk}^{feasible,quantity}$, by,

$$ARR_{sk}^{feasible,quantity} = ARR_{sk}^{positive,quantity} \times PFRF_{ISO} \tag{5.11}$$

5.3.4 Reductions of Feasible Auction Revenue Rights to Satisfy Base Load Limit on Financial Transmission Rights

In FABS, ISO intends to allocate ARRs to LSEs so that they can hedge against their FTR acquisition costs. Moreover, ISO intends to auction FTRs for LSEs so that they can hedge against their transmission congestion costs. The auctioned FTRs are intended to provide a hedge up to a maximum of base load requirements of LSEs. Therefore, before allocating ARRs to LSEs, ISO has to make sure that an LSE's sum of allocated ARRs does not exceed its base load requirement. This is termed base load limit on Financial Transmission Rights.

When an LSE's base load requirement, Ld_k^{base}, is more than its sum of feasible ARRs, $\sum_{s=1}^{S} ARR_{sk}^{feasible,quantity}$, then ISO allows allocation of feasible ARRs to the LSE. However, if an LSE's sum of feasible ARRs, $\sum_{s=1}^{S} ARR_{sk}^{feasible,quantity}$, exceeds its base load requirement, Ld_k^{base}, then ISO proportionately reduces the feasible ARRs. For proportionate reduction, ISO calculates a feasible ARR reduction factor, $FARF_{ISO}$, by,

$$FARF_{ISO} = \frac{Ld_k^{base}}{\sum_{s=1}^{S} ARR_{sk}^{feasible,quantity}} \tag{5.12}$$

ISO determines allocated ARR quantities of LSE at node *k*, $ARR_{sk}^{allocated,quantity}$, by,

$$ARR_{sk}^{allocated,quantity} = \begin{cases} ARR_{sk}^{feasible,quantity} & , \sum_{s=1}^{S} ARR_{sk}^{feasible,quantity} \leq Ld_k^{base} \\ ARR_{sk}^{feasible,quantity} \times FARF_{ISO} & , \sum_{s=1}^{S} ARR_{sk}^{feasible,quantity} > Ld_k^{base} \end{cases} \tag{5.13}$$

In FABS, ISO publicly announces allocated ARR quantities. Moreover, ISO allows Financial Bilateral Transactions up to the allocated ARR quantities. GenCos and LSEs assume that, under normal operating conditions, Financial Bilateral Transactions up to the allowed ARR quantities do not risk reductions by ISO because they have passed a Simultaneous Feasibility Test.

After annual ARR allocation, ISO invites bids for annual FTR auction. Next section explains how each LSE privately determines its FTR bids to suit its profit-seeking goals and risk-aversion preferences.

5.4 Optimization of Bids for Financial Transmission Rights

Bidding for FTRs is an investment decision that demands careful evaluation of risk-return trade-offs of FTRs by LSEs. In FTR bid optimization process, an LSE seeks to determine optimal FTR bid prices that maximize return of FTRs as well as minimize associated risks. An LSE needs to evaluate its expected return for each FTR. These expected returns count towards the “return” aspect in the risk-return trade-off. For the “risk” aspect of the risk-return trade-off, an LSE needs to evaluate risks of variance in return of each FTR as well as covariances between returns of all FTRs.

FTR bids of an LSE consist of following data:

i. the FTR source and sink nodes, s and k
ii. the LSE’s bid quantity for FTR from s to k, $FTR_{sk}^{bid,quantity}$ in MW
iii. the LSE’s bid price for FTR from s to k, $FTR_{sk}^{bid,price}$ in \$/MW
iv. the FTR duration (same as decision period of the annual FTR auction)

In FABS, an LSE determines quantities and prices of its FTR bids, as explained in Sections 5.4.1 and 5.4.2 respectively.

5.4.1 Determination of Possible FTR Bid Quantities

In FABS, as mentioned earlier, ISO intends to auction FTRs for LSEs to use as hedge against their transmission congestion costs in meeting their base load requirements. In consequence, ISO requires that sum of FTR bids of on LSE, $\sum_{s=1}^{S} FTR_{sk}^{bid,quantity}$, should not exceed its base load requirement, Ld_k^{base}. As a result, during determination of its FTR bid quantities, an LSE has to satisfy the constraint as follows,

$$\sum_{s=1}^{S} FTR_{sk}^{bid,quantity} \leq Ld_k^{base} \tag{5.14}$$

When an LSE’s base load requirement, Ld_k^{base}, is equal to its sum of allocated ARRs, $\sum_{s=1}^{S} ARR_{sk}^{allocated,quantity}$, then LSE chooses its FTR bid quantities to be the same as its corresponding allocated ARR quantities.

The LSE chooses these FTR bid quantities because ARRs allocated by ISO not only provide a perfect hedge to the LSE against acquisition cost of FTRs, but FTR bid quantities also satisfy constraint (5.14). An LSE’s allocated ARR quantity between two nodes determines its maximum feasible bilateral transaction between the two nodes. However, LSEs are unaware of their actual Financial Bilateral Transactions before submitting FTR bids to ISO because LSEs agree on Financial Bilateral Transactions after announcement of FTR auction clearing results. Therefore, LSEs determine their FTR bid quantities depending on their known base loads and already allocated ARRs instead of unknown bilateral transaction requirements. LSEs have to pay transmission congestion costs to ISO for bilateral transactions that use transmission network. Since both FTRs and bilateral transactions have well defined source and sink nodes, if power quantity of a bilateral transactions is less than or equal to the corresponding FTR then LSE is perfectly hedged against the resulting transmission congestion costs because it receives equal FTR credits.

Although an LSE that bids for FTRs is not guaranteed to secure any bilateral transactions, if it wins FTRs then it is not bound to undertake a Financial Bilateral Transaction, from source node to sink node of the FTR, to obtain an FTR credit payment from ISO. An LSE's FTR credit payment is also independent of power flows, from source node to sink node of FTR, that result from trading decisions in day-ahead auction. Consequently, an LSE can use its FTR credit payments from ISO to offset, if not perfectly hedge against, transmission congestion costs of meeting its base load requirement through day-ahead auction, as explained next.

For energy traded through day-ahead auction, LSEs pay ISO at the rate of LMPs at their local nodes. However, a component of LMP paid by an LSE covers transmission congestion costs of delivering energy to its node. Therefore, if an LSE holds FTRs then it should be able to offset the transmission congestion component of its payment to ISO. However, since an LSE that buys base load in day-ahead auction does not know what portions of its base load will flow from which source nodes in a particular trading interval, acquiring FTR bid quantities does not guarantee perfect hedge against the transmission congestion costs.

If an LSE's base load requirement is equal to its sum of allocated ARRs then, to avoid violation of constraint (5.14), the LSE should not increase its FTR bid quantities above the corresponding allocated ARR quantities. However, if an LSE's sum of allocated ARRs, $\sum_{s=1}^{S} ARR_{sk}^{allocated,quantity}$, is less than its base load requirement, Ld_k^{base}, then LSE can increase its FTR bid quantities, as far as constraint (5.14) is not violated.

By increasing FTR bid quantities above allocated ARRs, an LSE is not hedged against FTR acquisition costs of its complete FTR bid quantities. Despite the imperfect hedge, an LSE increases the FTR bid quantities in FABS, due to following reasons. An LSE safeguards against the imperfect hedge by carefully evaluating risk-return trade-off of FTRs during determination of FTR bid prices, as will be described in Section 5.4.2. FTR bids are increased above maximum feasible bilateral transactions because FTRs can not only provide perfect hedge against transmission congestion costs of Financial Bilateral Transactions but can also offset transmission congestion costs of energy traded in the day-ahead auction. Moreover, an LSE increases its FTR bid quantities in an attempt to hedge against transmission congestion costs of meeting its base load requirements because a more sophisticated solution is beyond the scope of this thesis.

In FABS, an LSE increases its FTR bid quantities depending on its known base loads and already allocated ARRs instead of unknown bilateral transaction requirements. Since sum of allocated ARRs, $\sum_{s=1}^{S} ARR_{sk}^{allocated,quantity}$, is less than base load requirement, Ld_k^{base}, an LSE determines its FTR bid quantities, that sum up to its base load, by proportionately increasing the corresponding allocated ARRs. For the proportionate increase, LSE at sink node *k* calculates an FTR quantity increase factor, $FQIF_k$, by,

$$FQIF_k = \frac{Ld_k^{base}}{\sum_{s=1}^{S} ARR_{sk}^{allocated,quantity}} \tag{5.15}$$

Consequently, depending on whether an LSE's sum of allocated ARRs, $\sum_{s=1}^{S} ARR_{sk}^{allocated,quantity}$, is less than or equal to its base load requirement, Ld_k^{base}, the

LSE determines its FTR bid quantity between source node *s* and sink node *k*, $FTR_{sk}^{bid,quantity}$, by

$$FTR_{sk}^{bid,quantity} = \begin{cases} ARR_{sk}^{allocated,quantity} & , \quad \sum_{s=1}^{S} ARR_{sk}^{allocated,quantity} = Ld_k^{base} \\ ARR_{sk}^{allocated,quantity} \times FQIF_k & , \quad \sum_{s=1}^{S} ARR_{sk}^{allocated,quantity} < Ld_k^{base} \end{cases} \tag{5.16}$$

5.4.2 Determination of Optimal FTR Bid Prices

LSEs optimize their FTR bid prices and submit these to the ISO as the prices they are willing to pay. In FTR bid optimization process, an LSE seeks to determine optimal FTR bid prices that maximize return of FTRs as well as minimize associated risks. An LSE can calculate expected returns for holding FTRs on the basis of expected LMPs at source and sink nodes. Additionally, an LSE can use variances and covariances of LMPs at all nodes and private risk aversion factor to determine risks of holding FTRs. An LSE needs to optimize its FTR bid price to achieve best trade-off between minimizing risk and maximizing return of an FTR. This section presents a new FTR bid price optimization method to achieve the risk-return trade-off.

Return characteristics include expectation, E, variance, σ^2, and covariance, σ, of returns for all risky FTR investments. For determining the return characteristics, an LSE needs to do statistical analysis of LMPs in the previous year, which involves determination of expectation, E, variance, σ^2, and covariance, σ, of LMPs for all nodes, as shown in Section 5.2. Return characteristics of risky FTR investments are determined in Sections 5.4.2.1, 5.4.2.2 and 5.4.2.3.

5.4.2.1 Returns and Expected Returns for Financial Transmission Rights

Equation (5.1) is used to develop an expression of LSE's return for an FTR. Assuming that decision period has a total of *Z* trading intervals, FTR revenue of LSE is calculated as $\sum_{z=1}^{Z} FTR_{sk}^{bid,quantity} \times \left(\lambda_{k,z} - \lambda_{s,z}\right)$ where $\lambda_{k,z}$ and $\lambda_{s,z}$ are LMPs, in trading interval z, at sink node s and source node s respectively and $FTR_{sk}^{bid,quantity}$ is FTR bid quantity. FTR acquisition cost of LSE, over all trading intervals, depends on FTR expenses as well as ARR credits, as calculated by,

$$Cost = FTR\ Expenses - ARR\ Credits \tag{5.17}$$

Total FTR expenses for FTR bid quantity, $FTR_{sk}^{bid,quantity}$, and FTR bid price, $FTR_{sk}^{bid,price}$, between source node s and sink node k, are expressed as,

$$FTR_{sk}^{bid,quantity} \times FTR_{sk}^{bid,price} \tag{5.18}$$

where $FTR_{sk}^{bid,price}$ covers all trading intervals in the decision period. As a result, equation (5.18) does not require a summation over a total of Z trading intervals.

Given that LSE holds allocated ARRs between sink node k and source node s, $ARR_{sk,\max}^{allocated,\,quantity}$, ARR credit payments from ISO to LSE are calculated as,

$$ARR_{sk}^{allocated,quantity} \times FTR_{sk}^{bid,price} \tag{5.19}$$

Using equation (5.17), formula for FTR expenses (5.18) and formula for ARR credits (5.19) as well as combining like terms yields following expression for FTR acquisition cost,

$$\left(FTR_{sk}^{bid,quantity} - ARR_{sk}^{allocated,quantity}\right) \times FTR_{sk}^{bid,price} \tag{5.20}$$

Substituting the expressions for revenue and cost of local bilateral transaction into equation (5.1), gives following equation for return of FTR between sink node k and source node s, r_{sk},

$$r_{sk} = \frac{\sum_{z=1}^{Z} FTR_{sk,\max}^{bid,quantity} \times \left(\lambda_{k,z} - \lambda_{s,z}\right)}{\left(FTR_{sk}^{bid,quantity} - ARR_{sk}^{allocated,quantity}\right) \times FTR_{sk}^{bid,price}} - 1 \tag{5.21}$$

Since an LSE can choose $FTR_{sk}^{bid,quantity}$ to be equal to $ARR_{sk}^{allocated,quantity}$, ($FTR_{sk}^{bid,quantity} - ARR_{sk}^{allocated,quantity}$) can lead to division by zero in (5.21). For simplicity, this thesis assumes that an LSE's operating costs of FTR bid optimization process offset ARR credits of 0.1% of $ARR_{sk}^{allocated,quantity}$. As a result of the assumed operating costs, an LSE only takes into account ARR credits of the remaining 99.9% of $ARR_{sk}^{allocated,quantity}$. Therefore, $ARR_{sk}^{allocated,quantity}$ is reduced to 99.9% of its value before being used in equation (5.21), or any other equations derived from it. Consequently, above mentioned possibility of division by zero is eliminated. Moreover, note that an LSE's FTR bid optimization determines optimal FTR bid price, $FTR_{sk}^{bid,price}$, as the maximum price that it is willing to pay if its FTR bid is cleared by ISO. Therefore, $FTR_{sk}^{bid,price}$ in the denominator of equation (5.21) is the decision variable for FTR bid optimization. Equation (5.21) is applicable over a total of Z trading intervals. At the time of FTR bid optimization, allocated ARR quantity, $ARR_{sk}^{allocated,quantity}$, and FTR bid quantity, $FTR_{sk}^{bid,quantity}$, are assumed certain. However, values of $\lambda_{k,z}$ and $\lambda_{s,z}$ are uncertain because they represent LMPs, in interval z, at sink node k and source node s respectively. Note that the values of both LMPs can vary between trading intervals.

In this thesis, FTR bid optimization considers overall variations of LMPs, irrespective of trading interval of the decision period. However, it does not consider variations in LMPs at the same node between trading intervals that have different time-of-day or time-of-year characteristics, as explained next. According to time-of-year, a trading interval may be defined as a winter or summer interval but seasonal variations are not modelled in FABS. Similarly, in terms of time-of-day, a trading interval can be defined as a peak or an off-peak interval but our FTR bid optimization model gives the same solution for all trading intervals in the decision period. Due to uncertain values of $\lambda_{k,z}$ ($\lambda_{s,z}$) in trading intervals of the decision period in future, λ_k (λ_s) is defined as a random variable to represent overall variable LMP, irrespective of trading interval, at sink node *k* (source node *s*). Values of these random variables are unknown until ISO determines LMPs as a result of DC-OPF for day-ahead auction. Since each GenCo independently increases/decreases its price-sensitive supply offers in response to its private profit from the day-ahead auction in FABS, LMP values are uncertain and may randomly vary between limits applied by ISO. However, a nodal LMP's random variable is not completely random but rather follows an approximately normal distribution – that can be adequately represented by expectation and variance of the LMP. Substituting λ_k (λ_s) for $\lambda_{k,z}$ ($\lambda_{s,z}$), in (5.21) yields,

$$r_{sk} = \frac{\sum_{z=1}^{Z} FTR_{sk,\max}^{bid,quantity} \times \left(\lambda_k - \lambda_s\right)}{\left(FTR_{sk}^{bid,quantity} - ARR_{sk}^{allocated,quantity}\right) \times FTR_{sk}^{bid,price}} - 1 \tag{5.22}$$

Due to the uncertainty of random variables λ_k and λ_s, expected return for an FTR is not the same as return of an FTR represented by (5.22). Expectation of the return, $E(r_{sk})$, depends on expectation of LMP at sink node, $E\left(\lambda_k\right)$, and source node, $E\left(\lambda_s\right)$. Substituting $E\left(\lambda_k\right)$ and $E\left(\lambda_s\right)$ for λ_k and λ_s in (5.22) leads to,

$$E_{sk} = E(r_{sk}) = \frac{\sum_{z=1}^{Z} FTR_{sk,\max}^{bid,quantity} \times \left(E\left(\lambda_k\right) - E\left(\lambda_s\right)\right)}{\left(FTR_{sk}^{bid,quantity} - ARR_{sk}^{allocated,quantity}\right) \times FTR_{sk}^{bid,price}} - 1 \tag{5.23}$$

$$s = 1, \cdots, S, s \neq k$$

An LSE needs to evaluate its expected return for each FTR, as explained above. The expected returns count towards the "return" aspect in the risk-return trade-off evaluated by FTR bid optimization, as discussed in introduction of this Chapter.

5.4.2.2 Variance of Returns from Financial Transmission Rights

In addition to evaluating the "return" aspect in the risk-return trade-off, an LSE needs to evaluate the "risk" aspect. The risk evaluation involves calculation of variance in return of each FTR as well as covariance between returns of all FTRs.

In order to develop equation for variance of return for an FTR, equation (5.22) is rearranged, to clearly see random variables and their coefficients as well as any constants,

$$r_{sk} = \left\{ \frac{\sum_{z=1}^{Z} FTR_{sk,\max}^{bid,quantity}}{\left(FTR_{sk}^{bid,quantity} - ARR_{sk}^{allocated,quantity} \right) \times FTR_{sk}^{bid,price}} \right\} \left(\lambda_k - \lambda_s \right) - 1 \qquad (5.24)$$

As equation (5.24) shows, random variables of LMPs at sink node *k* and source node *s*, λ_k and λ_s, introduce uncertainty in return of the corresponding FTR. For that reason, buying FTRs is a risky endeavour that demands a careful risk assessment. Variance is a measure of risk that can be used for the risk analysis. Equation (5.24) is a function of two random variables and variance has following property for such functions of two random variables,

$$Var\left(a\left(X - Y \right) + b \right) = a^2 \left(Var\left(X \right) + Var\left(Y \right) - 2Cov\left(X, Y \right) \right) \qquad (5.25)$$

where *a* and *b* are constants and *X* and *Y* are random variables. Applying the property of variance (5.25) to equation (5.24) results in following expression for variance of return for FTR between sink node *k* and source node *s*, $\sigma^2(r_{sk})$,

$$\sigma_{sk}^2 = \sigma^2(r_{sk}) = \left\{ \begin{array}{l} \left(\dfrac{\sum_{z=1}^{Z} FTR_{sk,\max}^{bid,quantity}}{\left(FTR_{sk}^{bid,quantity} - ARR_{sk}^{allocated,quantity} \right) \times FTR_{sk}^{bid,price}} \right)^2 \\ \times \left(\sigma^2(\lambda_k) + \sigma^2(\lambda_s) - 2\sigma(\lambda_k, \lambda_s) \right) \end{array} \right\} \qquad (5.26)$$

$$s = 1, \cdots, S, s \neq k$$

5.4.2.3 Covariance between Returns of Financial Transmission Rights

In addition to variance of each return, covariance between returns of all FTRs can also contribute to risk. Therefore risk evaluation must explore covariance between returns of all FTRs, as discussed next.

Return of FTR between sink node *k* and source node *s* is shown in equation(5.24). Similarly, return of FTR between sink node *k* and another source node s', $r_{s'k}$, can be represented by,

$$r_{s'k} = \left\{ \frac{\sum_{z=1}^{Z} FTR_{s'k,\max}^{bid,quantity}}{\left(FTR_{s'k}^{bid,quantity} - ARR_{sk}^{allocated,quantity} \right) \times FTR_{s'k}^{bid,price}} \right\} \left(\lambda_k - \lambda_{s'} \right) - 1 \quad (5.27)$$

As equations (5.24) and (5.27) show, random variables of LMPs at sink node *k* as well as source nodes *s* and s' (i.e. λ_k, λ_s and $\lambda_{s'}$) introduce uncertainty in returns of the FTRs. Consequently, both FTRs are risky and relationship between the two risks can be evaluated by covariance. Both (5.24) and (5.27) are functions of two random variables and covariance has following property for such functions of two random variables,

$$Cov\left(a\left(X - Y \right) - b, c\left(X - Z \right) - b \right) = ac \begin{pmatrix} Var\left(X \right) - Cov\left(X, Z \right) \\ -Cov\left(Y, X \right) + Cov\left(Y, Z \right) \end{pmatrix} \quad (5.28)$$

where *a*, *b*, and *c* are constants and *X*, *Y* and *Z* are random variables. Applying the property of covariance (5.28) to (5.24) and (5.27) results in following expression for covariance between returns of FTRs, $\sigma(r_{sk}, r_{s'k})$,

$$\sigma_{sk,s'k} = \sigma(r_{sk}, r_{s'k})$$

$$= \left\{ \begin{array}{l} \left(\dfrac{\sum_{z=1}^{Z} FTR_{sk,\max}^{bid,quantity}}{\left(FTR_{sk}^{bid,quantity} - ARR_{sk}^{allocated,quantity}\right) \times FTR_{sk}^{bid,price}} \right) \\ \times \left(\dfrac{\sum_{z=1}^{Z} FTR_{s'k,\max}^{bid,quantity}}{\left(FTR_{s'k}^{bid,quantity} - ARR_{s'k}^{allocated,quantity}\right) \times FTR_{s'k}^{bid,price}} \right) \\ \times \left(\sigma^2(\lambda_k) - \sigma(\lambda_k, \lambda_s) - \sigma(\lambda_k, \lambda_{s'}) + \sigma(\lambda_s, \lambda_{s'}) \right) \end{array} \right\} \tag{5.29}$$

$$s = 1, \cdots, S, s \neq k, s' = 1, \cdots, S, s' \neq k, s' \neq s$$

5.4.2.4 Limits of Decision Variables

In practical markets, ISO enforces upper and lower limits on FTR bid prices submitted by market participants [12]. Therefore, in FABS, LSEs can only submit an FTR bid price, $FTR_{sk}^{bid,price}$, within a range specified by ISO. In this thesis, the range of valid bid price for an FTR is specified in terms of a reference FTR price, as explained next. Given the number of trading intervals of day-ahead market for which an FTR acts as hedge, Z, and the difference between expectation of LMPs at the sink and source nodes of the FTR, $\Delta\lambda_{sk}^{\exp}$, the reference FTR price is $Z \times \Delta\lambda_{sk}^{\exp}$. For simplicity, this thesis assumes that the range of valid bid price for an FTR extends from half of the reference FTR price to twice the reference FTR price. However, it is possible to change the limits of the range to other values. LSEs calculate lower limits of their decision variables, $FTR_{sk,\min}^{bid,price}$, by

$$FTR_{sk,\min}^{bid,price} = 0.5 \times Z \times \Delta\lambda_{sk}^{\exp} \tag{5.30}$$

and the upper limits, $FTR_{sk,\max}^{bid,price}$, as

$$FTR_{sk,\max}^{bid,price} = 2 \times Z \times \Delta\lambda_{sk}^{\exp} \tag{5.31}$$

5.4.2.5 Objective or Utility Function

An investor can develop an overall utility function of its investments, with the objective of maximizing expected returns and minimizing perceived risks of investments. This thesis uses overall utility function taken from [10] and expressed as,

$$U = E - \frac{1}{2} \cdot A \cdot R \tag{5.32}$$

where U is overall utility of investments, A is risk aversion factor of investor, E is overall expected return and R is overall perceived risk of investments. In equation (5.32), expected return quantity adds value to utility whereas perceived risk quantity causes loss of utility.

An investor can be risk neutral (A=0), or even a risk lover (A<0), but practical decision makers are normally risk averse (A>0). Following from [10], this thesis considers that A=3.0 is an average risk aversion factor of a market participant. In addition, this thesis assumes that A=4.0 is a high risk aversion factor. Based on a thumb rule explained in Appendix A, every market participant chooses its own risk aversion factor. Table A.4 lists risk aversion factors used by market participants at all nodes.

For LSE at node *k*, overall expected return, $E(r_k)$, is sum of its expected returns from all FTRs and expressed as,

$$E(r_k) = \sum_{s=1}^{S} E_{sk} \tag{5.33}$$

where *s* is a source node out of total *S* source nodes, *k* is sink node that is LSE's local node and E_{sk} is expected return for FTR between nodes *s* and *k*.

The LSE's overall variance of return, $\sigma^2(r)$, is determined by sum of its variance of returns for FTRs as well as covariance between returns of FTRs, as follows,

$$\sigma^2(r_k) = \sum_{s=1}^{S}\sum_{s'=1}^{S}\sigma_{sk,s'k} = \sum_{s=1}^{S}\sigma_{sk}^2 + \sum_{s=1}^{S}\sum_{\substack{s'=1 \\ s\neq s'}}^{S}\sigma_{sk,s'k} \tag{5.34}$$

where s is a source node and s' is a different source node ($s' \neq s$) out of total S source nodes, σ_{sk}^2 is variance of return for FTR from source node s and $\sigma_{sk.s'k}$ is covariance between returns of FTRs from source nodes s and s'.

Substituting expression of overall expectation from (5.33) and variance from (5.34) into overall utility function (5.32) leads to,

$$U_k = \sum_{s=1}^{S} E_{sk} - \frac{1}{2}A\left\{\sum_{s=1}^{S}\sigma_{sk}^2 + \sum_{s=1}^{S}\sum_{\substack{s'=1 \\ s\neq s'}}^{S}\sigma_{sk,s'k}\right\} \tag{5.35}$$

Equation (5.35) denotes overall utility of all FTRs of LSE at node k, U_k. The overall utility depends on E_{sk}, σ_{sk}^2 and $\sigma_{sk,s'k}$ that are expressed in (5.23), (5.26) and (5.29) respectively.

An LSE can obtain its optimal FTR bid prices by maximizing FTR utility (5.35) as follows,

$$\text{Maximize}_{FTR_{sk}^{bid,price},\,FTR_{s'k}^{bid,price}}\; U_k = \sum_{s=1}^{S} E_{sk} - \frac{1}{2}A\left\{\sum_{s=1}^{S}\sigma_{sk}^2 + \sum_{s=1}^{S}\sum_{\substack{s'=1 \\ s\neq s'}}^{S}\sigma_{sk,s'k}\right\} \tag{5.36}$$

subject to following upper and lower limits on the decision variables

$$\begin{aligned} FTR_{sk,\min}^{bid,price} &\leq FTR_{sk}^{bid,price} \leq FTR_{sk,\max}^{bid,price} \\ FTR_{s'k,\min}^{bid,price} &\leq FTR_{s'k}^{bid,price} \leq FTR_{s'k,\max}^{bid,price} \end{aligned} \tag{5.37}$$

$$s = 1, \cdots, S, s \neq k, s' = 1, \cdots, S, s' \neq k, s' \neq s$$

The optimization problem (5.36)-(5.37) can be solved by any standard non-linear programming solver. Matlab function for constrained non-linear programming, *fmincon*, is used to solve the FTR bid optimization problem in this thesis. The *fmincon* function requires user supplied initial values of decision variables and has capability to find a local solution, instead of a global solution. However, following methodology was used to attempt search of a global solution. During experimentation, randomly initialized decision variables were repeatedly supplied to *fmincon* function to check for existence of multiple extrema. Two extrema were identified but solution mostly converged to the stronger extremum. Furthermore, it was verified that when decision variables are initialized as explained in Section 5.6, solution converges to the stronger extremum.

5.5 Financial Transmission Rights Auction

In FABS, LSEs submit obligation FTR bids to ISO consisting of following data:

i. the FTR source and sink nodes, *s* and *k*
ii. the LSE's bid quantity for FTR from *s* to *k*, $FTR_{sk}^{bid,quantity}$ in MW
iii. the LSE's bid price for FTR from *s* to *k*, $FTR_{sk}^{bid,price}$ in \$/MW
iv. the FTR duration (same as decision period of the annual FTR auction)

ISO has an objective of maximizing revenue of the FTR auction subject to transmission network constraints as well as FTR quantity and price constraints submitted by LSEs. ISO uses DC transmission network model to clear the annual FTR auction in FABS. The FTR auction clearing method presented here is taken from [6]. During optimization of annual FTR auction, ISO's decision variable is FTR quantities (MW) to be cleared in the FTR market, $FTR_{sk}^{cleared,quantity}$. Based on FTR bid prices, $FTR_{sk}^{bid,price}$, submitted by LSEs, ISO determines its total revenue from cleared FTR quantities, $FTR_{sk}^{cleared,quantity}$, by summation over all bids,

$$\sum_{sk} FTR_{sk}^{bid,price} \cdot FTR_{sk}^{cleared,quantity} \tag{5.38}$$

ISO has to maximize its objective function (5.38) subject to transmission network constraints, as described next. Each transmission line *oe* from origin node *o* to end node *e*, has a physically limited power flow capacity, $Fl_{oe}^{capacity}$. Power flow on transmission line *oe*, from origin node *o* to end node *e*, due to cleared FTR quantity between source node *s* and sink node *k*, $FTR_{sk}^{cleared,quantity}$, can be determined by power transfer distribution factor, $PTDF_{oe,sk}$, as,

$$PTDF_{oe,sk} \cdot FTR_{sk}^{cleared,quantity} \tag{5.39}$$

Sum of power flows from origin node *o* to end node *e* of transmission line *oe*, due to cleared FTR quantities between all combinations of source and sink nodes, *sk*, is given by

$$\sum_{sk} PTDF_{oe,sk} \cdot FTR_{sk}^{cleared,quantity} \tag{5.40}$$

Sum of the power flows caused by cleared FTR quantities (5.40) should not exceed the power flow capacity of transmission line *oe*, $Fl_{oe}^{capacity}$,

$$\sum_{sk} PTDF_{oe,sk} \cdot FTR_{sk}^{cleared,quantity} \leq Fl_{oe}^{capacity} \tag{5.41}$$

Sum of reverse power flows through transmission line *oe*, from end node *e* to origin node *o*, due to cleared FTR quantities between all combinations of source and sink nodes, *sk*, should also be less than the power flow capacity of transmission line *oe*, $Fl_{oe}^{capacity}$,

$$\sum_{sk} -PTDF_{oe,sk} \cdot FTR_{sk}^{cleared,quantity} \leq Fl_{oe}^{capacity} \tag{5.42}$$

ISO's cleared FTR quantities should be such that the power flows conform to constraints (5.41) and (5.42) for all transmission lines in power transmission network.

In addition to satisfying transmission network constraints, each cleared FTR quantity between source node *s* and sink node *k*, $FTR_{sk}^{cleared,quantity}$, must be between zero and the corresponding FTR bid quantity, $FTR_{sk}^{bid,quantity}$,

$$0 \le FTR_{sk}^{cleared,quantity} \le FTR_{sk}^{bid,quantity} \tag{5.43}$$

ISO solves annual FTR auction problem, to determine cleared FTR quantities, by maximizing its objective function (5.38) as follows,

$$\text{Maximize} \sum_{sk} FTR_{sk}^{bid,price} \cdot FTR_{sk}^{cleared,quantity} \tag{5.44}$$

subject to

$$\begin{gathered} \sum_{sk} PTDF_{oe,sk} \cdot FTR_{sk}^{cleared,quantity} \le Fl_{oe}^{capacity} \\ \sum_{sk} -PTDF_{oe,sk} \cdot FTR_{sk}^{cleared,quantity} \le Fl_{oe}^{capacity} \\ 0 \le FTR_{sk}^{cleared,quantity} \le FTR_{sk}^{bid,quantity} \end{gathered} \tag{5.45}$$

The optimization problem (5.44)-(5.45) can be solved by any standard linear programming solver. Matlab function for linear programming, *linprog*, is used to solve the optimization problem in this thesis.

The solution of optimization problem (5.44)-(5.45) determines cleared FTR quantities. In terms of payable FTR prices, this thesis categorises an FTR auction as a pay-as-bid or pay-as-clear auction. In pay-as-clear FTR auction, participants pay for FTR at the rate of cleared FTR prices whereas in pay-as-bid FTR auction participants have to pay at the same rate as their FTR bid prices. In FABS, ISO determines cleared FTR prices ($/MW) from *s* to *k*, $FTR_{sk}^{cleared,price}$, as,

$$FTR_{sk}^{cleared,price} = \sum_{oe} \left[PTDF_{oe,sk} \cdot \left(\mu_{oe}^{+} - \mu_{oe}^{-} \right) \right] \tag{5.46}$$

where μ_{oe}^{+} and μ_{oe}^{-} are the shadow prices, also known as Lagrange multipliers, of transmission constraints (5.41) and (5.42) respectively. A transmission constraint's shadow price is the rate of change in objective function value when the capacity of the constraint infinitesimally increases or decreases [12]. FTR cleared prices are less than or equal to FTR bid prices of LSEs. FTR cleared prices ($/MW) are paid by LSEs to ISO for FTR cleared quantities (MWs). In FABS, FTR cleared prices are payable in monthly settlements during the decision period, i.e. coming year.

5.6 Case Studies

In this Chapter, two case studies are used to explore FTR bid price optimization method's potential to provide competitive advantage to an LSE, in terms of FTR cleared quantities, over its competitor LSEs. These case studies are also designed to show that if an LSE holds ARRs then its FTR acquisition costs are reduced. The two case studies are labelled as estimate FTR bidding and optimal FTR bidding. Status of every LSE in both case studies, in terms of holding ARRs and using the bid price optimization method, is listed as follows. The estimate FTR bidding represents the base case because it assumes that all LSEs have no ARRs or knowledge of the FTR bid price optimization method and only submit estimated FTR bid prices. By comparison, the optimal FTR bidding assumes that all LSEs use the optimization procedure and allocated ARRs to submit optimal FTR bid prices.

Complete data of a five node test grid used for simulation in FABS is provided in Appendix A. Although this thesis has presented a generic FTR bid optimization procedure, it has only tested the procedure on the five node test grid. Moreover, testing of the optimization procedure on larger grids is identified as future work. Each LSE's input data for its FTR bid price optimization is sent from Java environment of FABS to Matlab. The input data includes: (i) maximum allowed FTR bid quantities; (ii) available ARR hedge quantities; (iii) total number of trading intervals in the decision period; (iv) risk aversion factor of LSE; (v) upper and lower limits of decision variables; (vi) initial values of decision variables and (vii) expectations, variances as well as covariances of LMPs. Reference FTR prices were used as initial values of decision variables for all LSEs. An LSE's FTR bid optimization determines optimal bid prices for each FTR. The output of FTR bid optimization is retrieved from Matlab environment to Java based FABS.

5.7 Results

Only results of FTR bid price optimization by LSEs are discussed in this Chapter because this thesis does not focus on ISO's FTR auction and ARR allocation processes. LSE's allocated ARR quantities, FTR bid quantities and FTR reference prices, shown in Table 5.2, are required for discussing the results of FTR bid price optimization by LSEs. Note that three rows of Table 5.2 are blank because ISO does not allocate any ARRs for these three source-sink combinations, for reasons explained in 5.3.2. Table 5.2 shows that each allocated ARR quantity of LSE-1 exactly matches its respective FTR bid quantity. By contrast, each allocated ARR quantity of LSE-2 and LSE-3 is less than its respective FTR bid quantity. For example, Table 5.2 shows that LSE-2 has only 37MW allocated ARR quantity compared to 48MW FTR bid quantity between source Node-1 and sink Node-3. As a result, LSE-2's held ARR quantity is only 77% of the corresponding FTR bid quantity, between source Node-1 and sink Node-3. Similarly, LSE-2's held ARR quantities for other source-sink combinations are also 77% of the corresponding FTR bid quantities. In comparison, LSE-3's held ARR quantities for all source-sink combinations are only 62% of the corresponding FTR bid quantities.

Figure 5.1 shows FTR bid prices of LSEs as multiples of the reference FTR prices for both case studies. In case of estimate FTR bidding, all LSEs submit FTR bid prices equal to ISO's reference FTR prices because they are unaware of FTR bid price optimization procedure. By contrast, in optimal FTR bidding case study, possession of ARR quantities equal to FTR bid quantities enables LSE-1 to submit maximum allowed FTR bid prices, i.e. twice the reference FTR prices. However, LSE-2 and LSE-3 only submit reference FTR prices because they only hold 77% and 62% ARRs, respectively, as compared to their FTR bid quantities. Note that reference FTR prices were used as initial values of decision variables for all LSEs. The optimization algorithm did not find any better solution than the initial values, for LSE-2 and LSE-3.

Table 5.2 LSEs' Allocated ARR Quantities, FTR Bid Quantities and Reference FTR Prices

LSE Name	Source Node	Sink Node	Allocated ARR Quantity (MW)	FTR Bid Quantity (MW)	Reference FTR Price ($/MW)
LSE-1	Node-1	Node-2	37	37	1,428,192
	Node-3	Node-2	92	92	270,432
	Node-4	Node-2	35	35	1,014,336
	Node-5	Node-2	106	106	1,354,752
LSE-2	Node-1	Node-3	37	48	1,157,760
	Node-3	Node-3	-	-	-
	Node-4	Node-3	35	46	743,904
	Node-5	Node-3	106	138	1,084,320
LSE-3	Node-1	Node-4	31	50	413,856
	Node-3	Node-4	-	-	-
	Node-4	Node-4	-	-	-
	Node-5	Node-4	88	144	340,416

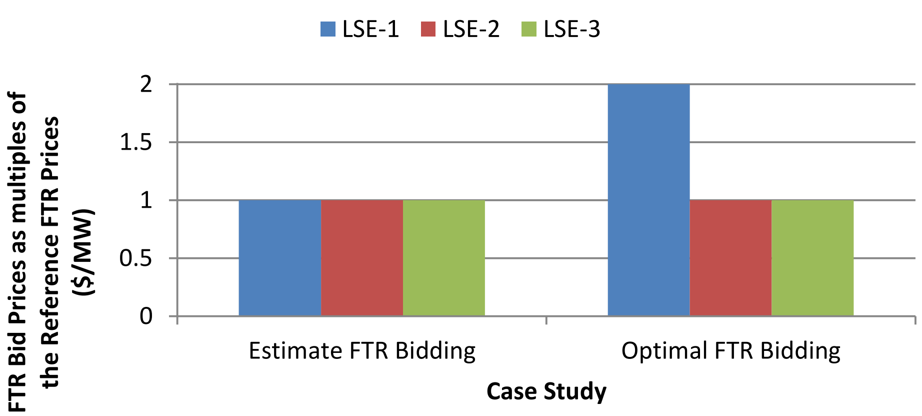

Figure 5.1 FTR Bid Prices of LSEs as multiples of the Reference FTR Prices

Cleared FTR quantities by ISO are shown in Figure 5.2. In case of estimate FTR bidding, sum of cleared FTR quantities of LSE-1, LSE-2 and LSE-3 is 164MW, 232MW and 196MW respectively. With optimal FTR bidding, the sum of cleared FTR quantities increases from 164MW to 270MW for LSE-1, decreases from 232MW to 181MW for LSE-2 but remains the same for LSE-3 because of following reasons. Supported by ARR quantities exactly matching respective FTR bid quantities, LSE-1 manages to submit competitive FTR bid prices compared to other LSEs. In contrast, FTR bid prices of LSE-2 are less competitive because LSE-2's held ARR quantities are only 77% of the corresponding FTR bid quantities. Consequently, LSE-1 gains advantage over LSE-2 in terms of the sum of cleared FTR quantities.

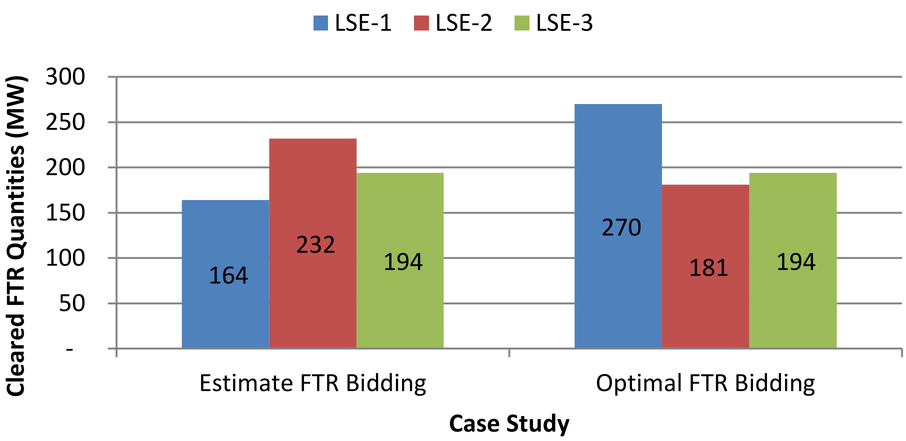

Figure 5.2 Cleared FTR Quantities by ISO

Figure 5.3 presents comparison of FTR expenses, ARR credits and FTR acquisition costs of LSE-1. In absence of ARR credits in estimate FTR bidding, $217million FTR expenses account for FTR acquisition costs. Note that ARR credits reduce FTR acquisition costs because they offset expenses of buying cleared FTRs. Since LSE-1 has sufficient ARR credits to completely offset FTR expenses in optimal FTR bidding case, FTR acquisition costs are reduced to zero, as illustrated by Figure 5.3. As a result, LSE-1 is completely hedged against uncertain FTR acquisition costs.

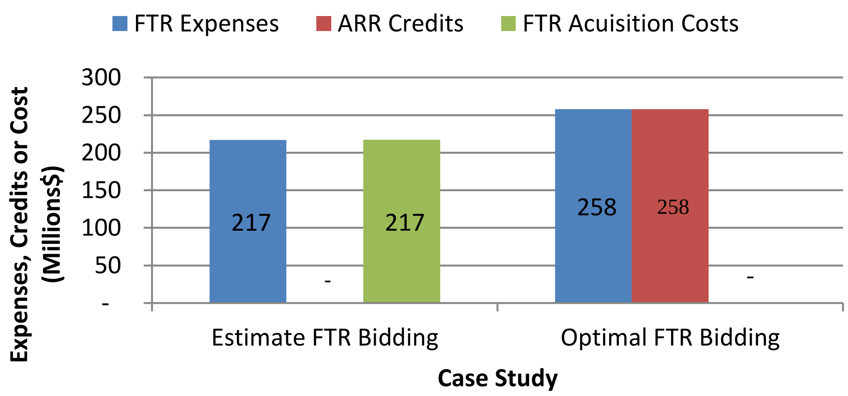

Figure 5.3 Comparison of FTR Expenses, ARR Credits and FTR Acquisition Costs of LSE-1

Comparison of FTR expenses, ARR credits and FTR acquisition costs of LSE-3 are shown in Figure 5.4. Due to lack of ARR credits in estimate FTR bidding, FTR expenses of $69million account for FTR acquisition costs. However, for optimal case, since LSE-3's $42million ARR credits are less than $69million FTR expenses, it has to pay the difference of $27million as FTR acquisition costs. Comparison of estimate and optimal FTR bidding cases shows that optimization procedure and allocated ARRs enable LSE-3 to reduce its FTR acquisition costs from $69million to only $27million. Note that in both cases cleared FTR quantities of LSE-3 remain 194MW, as illustrated in Figure 5.2.

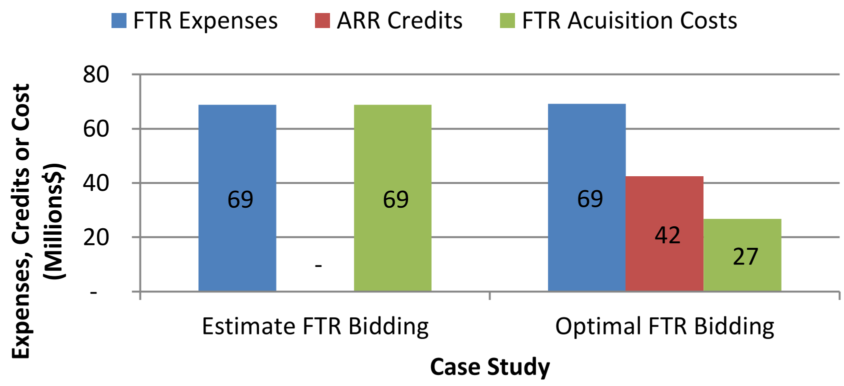

Figure 5.4 Comparison of FTR Expenses, ARR Credits and FTR Acquisition Costs of LSE-3

5.8 Conclusions

Using information provided in training manual [11], a mathematical model of ARR allocation is obtained. As an original contribution, mathematical model of FTR bid optimization process is developed. During its FTR bid optimization, each LSE strives to find optimal FTR bid prices that maximize return of FTRs but minimize associated risks. However, mathematical model of FTR auction is taken from [6] and the three mathematical models, mentioned in this paragraph, are incorporated in FABS.

If a market participant fails to develop a competitive FTR bid price then it faces risk of losing FTR cleared quantities to its competitors. The optimal FTR bidding method empowers a market participant to compete in the FTR market for more FTR quantities. If a market participant holds ARRs then it can hedge against the uncertain cost of FTR acquisition.

5.9 References

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6 Portfolio Optimization Procedures for Generators and Loads

6.1 Introduction

In practical wholesale electricity markets of North America, decentralized bilateral transactions complement organized day-ahead auction. Market participants may find it beneficial to secure bilateral energy transactions, in advance of day-ahead auction, for hedging risks of price volatility and revenue uncertainty. However, organized day-ahead auction is necessary for two reasons: (i) system operator needs to ensure that generation balances transmission losses and load demands at time of delivery and (ii) market participants may not be able to fulfil their energy trading requirements through bilateral transactions alone.

The markets of North America use Locational Marginal Price (LMP) where hourly price of day-ahead market at each node can be different from other nodes due to congestion and losses on transmission network. Each power Generation Company (GenCo) and Load Serving Entity (LSE) participates in the wholesale market as a seller and a buyer respectively. In addition, an LMP market must have an independent system operator (ISO) to organize day-ahead auction and regulate flows of power quantities due to decentralized bilateral transactions over transmission network. If power quantities of bilateral transactions, requested by market participants, are not regulated by ISO then there can be two problems: (i) power flows over transmission lines may exceed their normal operating capacities and lead to overloading of transmission system or (ii) some LSEs may be deprived of their full load demand to avoid the overloading of transmission system. ISO is responsible for secure operation of the overall power system while providing all participants with opportunities to benefit from physically limited transmission capacities.

As discussed in Chapter 5, ISO conducts a Simultaneous Feasibility Test as a part of its annual ARR allocation process in FABS - “Financial transmission instruments, energy Auction and Bilateral transaction Simulator for wholesale electricity markets”. The Simultaneous Feasibility Test inherently ensures that each Load Serving Entity has equitable access to physically limited transmission capacities. Equitable access of a Load Serving Entity is proportional to its share of previous peak system load. Based on the Simultaneous Feasibility Test, ISO announces maximum levels of simultaneously feasible Financial Bilateral Transactions. Despite the simultaneous feasibility check, ISO may have to reduce quantities of Financial Bilateral Transactions (requested by market participants) in case of unforeseen circumstances like transmission and generation failures. However, the Financial Bilateral Transactions are not reduced in FABS because it does not model power system failures. It is important to remember that only direct-search Financial Bilateral Transactions between market participants, at the same node or at different nodes, are modelled in FABS.

Once ISO announces results of Simultaneous Feasibility Test, each seller and buyer undertakes individual decision making about how much power quantity to invest in which particular bilateral transaction and how much power quantity to allocate to the day-ahead auction. The participants are allowed to mutually agree on prices and quantities of bilateral transactions, subject to upper limits on transfer capacities, without any liability to disclose details of their private endeavours. This decision making involves portfolio optimization that is very crucial to successfully maximize own profits and constrain risks to personal risk aversion levels.

For portfolio optimization, a market participant needs to evaluate its expected return for each trading option. These expected returns count towards the “return” aspect in the risk-return trade-off. For the “risk” aspect of the risk-return trade-off, a GenCo needs to evaluate risks of variance in return of each trading option as well as covariance between returns of all trading options.

Since bilateral transactions are privately conducted, participants of practical deregulated electricity markets do not provide information on their decision making practices for bilateral transactions. However, portfolio optimization can serve as a powerful tool for managers of GenCos and LSEs who can follow its reasoning, perhaps with slight variations, in their decision making processes. Portfolio optimization has been successfully applied for direct-search Financial Bilateral Transactions of GenCos in [1, 2] and LSEs in [3]. Since portfolio optimization is separately conducted by each market participating entity, it is highly suitable for self-determining agents in agent-based developments. Although, applications of portfolio optimization in [1, 2] or [3] are not agent-based, research presented in this thesis has used portfolio optimization in agent-based software – FABS. Portfolio optimization model in [1] does not consider maximum levels of simultaneously feasible Financial Bilateral Transactions. The model in [1] is used as the basic portfolio optimization model of a GenCo in FABS. Moreover, maximum levels of simultaneously feasible Financial Bilateral Transactions are included in the basic portfolio optimization model of a GenCo to develop improved portfolio optimization model for FABS.

Portfolio optimization model of LSE in [3] involves modelling of an LSE's retail operations. However, portfolio optimization model of LSE in [3] is not useful because FABS focuses on wholesale electricity market and does not model retail operations. Therefore, a basic portfolio optimization model of an LSE is developed for FABS on the pattern of the basic portfolio optimization model of GenCo in [1]. Financial Transmission Rights and simultaneous feasibility constraints are incorporated in the basic portfolio optimization model of an LSE to design the improved portfolio optimization model of an LSE in FABS.

The rest of the chapter is organized as follows. Section 6.2 presents both the basic and improved portfolio optimization models of a Generation Company. A summary of a Generation Company's portfolio optimization procedure is presented in Section 6.3. Section 6.4 presents both the basic and improved portfolio optimization models of a Load Serving Entity. A summary of a Load Serving Entity's portfolio optimization procedure is presented in Section 6.5. Section 6.6 presents case studies of this Chapter, whereas results and conclusions are presented in Section 6.8 and Section 6.8 respectively.

6.2 Basic and Improved Models of Portfolio Optimization for a Generation Company

Total power generation capability of a GenCo is called its *Capacity*. GenCo g can trade its *Capacity*, $p_g^{\max}$, through a number of trading options. In order to develop generic basic and improved portfolio optimization models, it is decided to consider as many bilateral transaction options as the number of nodes, N, in a power system. The generic basic and improved models are valid irrespective of the number or location of LSEs in the power system. Both models assume that a maximum of one LSE is connected to any node of the power system and can also accommodate nodes without LSEs. In addition, the option to trade by submitting price-sensitive supply offers in day-ahead auction is included in the generic models. As a result, both generic portfolio optimization models consider a total of N+1 trading options.

Portfolio optimization of a GenCo determines optimal allocation of its *Capacity* among N+1 trading options. Decision or unknown variables of portfolio optimization by GenCo g are the fractions of its *Capacity*, $p_g^{\max}$, allocated to N+1 trading options. In order to solve its portfolio optimization problem, a GenCo must assume energy prices of its trading options and know upper limits of its decision variables. To find the upper limits of decision variables, however, a GenCo first needs to determine maximum feasible power quantity allocations for all trading options. The maximum feasible power quantity allocations are also required to evaluate expectation, variance and covariance of return (collectively termed return characteristics) for trading options.

Calculation methods for maximum feasible power quantity allocations, upper limits of decision variables and return characteristics of all trading options are covered in Sections 6.2.1, 6.2.2 and 6.2.3 respectively.

6.2.1 Maximum Feasible Power Quantity Allocations to Trading Options

Direct-search Financial Bilateral Transactions of a GenCo can be divided into two types: (i) bilateral transaction with LSE at local node and (ii) bilateral transactions with LSEs at non-local nodes. Since a GenCo is not responsible for transmission congestion costs, its non-local Financial Bilateral Transactions are free from risk of uncertain transmission congestion costs. Local Financial Bilateral Transactions are also risk-free because they do not use transmission network. The two types of a GenCo's direct-search Financial Bilateral Transactions are termed risk-free non-local and risk-free local Financial Bilateral Transactions respectively.

In addition to these two types of Financial Bilateral Transactions, a GenCo can trade energy by submitting price-sensitive supply offers in day-ahead auction. Price-sensitive supply offers are submitted by GenCos and processed by ISO to determine which ones are most competitive (lowest priced) and should be accepted. Price-sensitive supply offer of a GenCo represent its willingness to sell specified power quantities if it can get energy prices that are higher or equal to its specified energy prices. A GenCo's participation in day-ahead energy auction is a risky option because market prices can fluctuate unpredictably and it has to compete with other GenCos in the market. ISO will not accept price-sensitive supply offers of a GenCo if it finds that energy prices offered by other GenCos are lower and thus more competitive.

Discussion of maximum feasible power quantity allocations for risky day-ahead auction is covered in Section 6.2.1.1. If a bilateral transaction option is infeasible due to absence of any LSE at a particular node then maximum feasible power quantity allocation of the trading option is set to zero. Otherwise, maximum feasible power quantity allocations for risk-free non-local and local Financial Bilateral Transaction options are determined as discussed in Section 6.2.1.2 and Section 6.2.1.3 respectively.

6.2.1.1 Risky day-ahead auction

For day-ahead auction, although ISO has an upper limit on energy prices in price-sensitive supply offers of GenCos, it does not enforce limits on power quantities that GenCos can offer. Therefore, if a GenCo cannot secure a bilateral transaction then it has an option to offer its *Capacity*, $p_g^{\max}$, in day-ahead auction. In both basic and improved portfolio optimization models, maximum feasible power quantity allocation for the day-ahead auction, $p_{ln,\max}^{DAA}$, is set as,

$$p_{ln,\max}^{DAA} = p_g^{\max} \tag{6.1}$$

6.2.1.2 Risk-free non-local Financial Bilateral Transactions

The basic model [1] ignores maximum quantities of simultaneously feasible Financial Bilateral Transactions announced by ISO for GenCo *g*. It assumes that GenCo *g*'s *Capacity*, $p_g^{\max}$, can be allocated to a non-local Financial Bilateral Transaction. In consequence, maximum feasible power quantity allocation to non-local transaction with LSE at node *i*, $p_{i,\max}^{FBT}$, is set as follows,

$$p_{i,\max}^{FBT} = p_g^{\max} \tag{6.2}$$

However, the assumption of basic model is not valid for practical power systems, as ISO can reduce non-local bilateral transactions if they are not simultaneously feasible. These reductions are loss of bilateral transaction opportunity for market participants. If GenCo had adhered to simultaneous feasibility constraints announced by ISO then it could have allocated lost opportunity fraction of its *Capacity* to alternative bilateral transaction options. It is important to improve the basic portfolio optimization model of a GenCo to avoid the reductions by ISO and the consequent opportunity losses to GenCos.

The improved model considers maximum quantities of simultaneously feasible Financial Bilateral Transactions announced by ISO for a GenCo. This quantity is used as maximum quantity of GenCo's feasible Financial Bilateral Transaction, publicly announced by ISO, with LSE at node *i*, denoted as $p_{i,\max}^{SFT}$. The maximum feasible power quantity allocation for non-local transaction, privately determined by GenCo, with LSE at node *i* is denoted as $p_{i,\max}^{FBT}$. A GenCo seeks to determine the value of its $p_{i,\max}^{FBT}$ by considering $p_{i,\max}^{SFT}$ as shown in following equation,

$$p_{i,\max}^{FBT} = \begin{cases} p_g^{\max}, p_g^{\max} < p_{i,\max}^{SFT} \\ p_{i,\max}^{SFT}, p_g^{\max} > p_{i,\max}^{SFT} \end{cases} \tag{6.3}$$

6.2.1.3 A risk-free local Financial Bilateral Transaction

The basic model ignores load requirement reported to GenCo *g* by its local LSE *l*, p_l^{local}, and assumes that local LSE *l* can buy GenCo *g*'s *Capacity*, $p_g^{\max}$. In basic model, maximum feasible power quantity allocation for the local bilateral (*lb*) transaction, $p_{lb,\max}^{FBT}$, is set as,

$$p_{lb,\max}^{FBT} = p_g^{\max} \tag{6.4}$$

In practical power systems, if load requirement of local LSE, p_l^{local}, is less than GenCo *g*'s *Capacity*, $p_g^{\max}$, then assumption of basic model will not hold. In such case, if GenCo allocates $p_g^{\max}$ to local transaction then it will face loss of opportunity. If GenCo had considered load requirement reported by local LSE, p_l^{local}, then it could have allocated lost opportunity fraction of its *Capacity* to alternative trading options. Therefore, the basic portfolio optimization model of a GenCo must be improved for local bilateral transaction to avoid the loss of opportunity.

The improved model considers maximum load requirement reported to GenCo *g* by its local LSE *l*, p_l^{local}. As a result, maximum feasible power quantity allocation for the local bilateral transaction, $p_{lb,\max}^{FBT}$, may be limited by p_l^{local} and can be determined as,

$$p_{lb,\max}^{FBT} = \begin{cases} p_g^{\max}, p_g^{\max} < p_l^{local} \\ p_l^{local}, p_g^{\max} > p_l^{local} \end{cases} \tag{6.5}$$

6.2.2 Upper limits of Decision Variables for Power Allocations to Trading Options

Once maximum feasible power quantity allocations are known for all trading options, it becomes possible to determine upper limits of decision variables for power allocations to the trading options. Decision or unknown variables of GenCo g's portfolio optimization are the power allocation fractions of its *Capacity*, $p_g^{\max}$, to N+1 trading options. For both basic and improved models, methods of determining upper limits of power allocation fractions of *Capacity* for trading options are the same. These methods for risky day-ahead auction and risk-free local and non-local Financial Bilateral Transactions are discussed next.

6.2.2.1 *Risky day-ahead auction*

Upper limit of power allocation fraction of GenCo g's *Capacity*, $p_g^{\max}$, for risky day-ahead auction, $x_{ln,\max}^{DAA}$, depends on value of maximum feasible power quantity allocation to the day-ahead auction, $p_{ln,\max}^{DAA}$. The upper limit is set as,

$$x_{ln,\max}^{DAA} = p_{ln,\max}^{DAA} \big/ p_g^{\max} \tag{6.6}$$

6.2.2.2 *Non-risky non-local Financial Bilateral Transactions*

Maximum feasible power quantity allocation to risk-free non-local Financial Bilateral Transaction with LSE at node i, $p_{i,\max}^{FBT}$, determines upper limit of power allocation fraction of GenCo g's *Capacity*, $p_g^{\max}$, to the bilateral transaction, $x_{i,\max}^{FBT}$,

$$x_{i,\max}^{FBT} = p_{i,\max}^{FBT} \big/ p_g^{\max} \tag{6.7}$$

6.2.2.3 A risk-free local Financial Bilateral Transaction

Upper limit of power allocation fraction of GenCo g's *Capacity*, $p_g^{\max}$, for risk-free local bilateral (*lb*) transaction, $x_{lb,\max}^{FBT}$, depends on value of maximum feasible power quantity allocation to the bilateral transaction, $p_{lb,\max}^{FBT}$. The upper limit is set as.

$$x_{lb,\max}^{FBT} = p_{lb,\max}^{FBT} \big/ p_g^{\max} \tag{6.8}$$

6.2.3 Return Characteristics of Trading Options

Return characteristics include expectation, E, variance, σ^2, and covariance, σ, of return for all trading options. For determining the return characteristics, a GenCo needs to do statistical analysis of LMPs from the previous year, which involves determination of expectation, E, variance, σ^2, and covariance, σ, of historical LMPs, as shown in Chapter 5. For determining the return characteristics, a GenCo also needs to calculate the quantities of the maximum feasible power allocations to all trading options, by formulae (6.1)-(6.5), presented in Section 6.2.1. For both basic and improved models, the return characteristics of day-ahead auction, as well as risk-free non-local and local bilateral transactions are determined in the same way as described next.

Equations for expected return from all N+1 trading options are derived first, and are followed by equations for variance and covariance of return. This order is followed because an expression for variance of return from a trading option depends on expression for expected return from the trading option. Similarly, an equation for covariance of returns depends on equations for expected return from all trading options.

6.2.3.1 Returns and Expected Returns for Trading Options

Each GenCo carries out its portfolio optimization for a specified decision period. The decision period can be a month, a year or any other length of time. A trading option's rate of return, in short return, is its benefit-to-cost ratio that is a measure of its financial performance. Benefit of a trading option is determined by the difference between its revenue and cost. In this section, revenue, cost and return refer to a specific trading option of a GenCo over a specified decision period. Return is defined by equation (5.1) that is used to develop expressions of returns for all trading options of a GenCo, as shown next.

Risk-free Local Financial Bilateral Transaction

Assuming that decision period has a total of Z trading intervals, revenue from local bilateral transaction with local LSE is calculated as $\sum_{z=1}^{Z} p_{lb,z}\pi_{lb,z}$ where $p_{lb,z}$ is power quantity and $\pi_{lb,z}$ is energy price for local bilateral (*lb*) transaction in trading interval z. Over all trading intervals, general expression for GenCo's cost of power generation is a quadratic function of the following form

$$C(\cdot)=\sum_{z=1}^{Z}\left(a_g\left(\cdot\right)^2+b_g(\cdot)+c_g\right) \tag{6.9}$$

where a_g, b_g and c_g are actual fuel consumption based coefficients of GenCo g. Therefore, from (6.9) the total cost of local bilateral transaction over all trading intervals is calculated as $\sum_{z=1}^{Z}\left(a_g\left(p_{lb,z}\right)^2+b_g p_{lb,z}+c_g\right)$, where $p_{lb,z}$ is power quantity allocated in trading interval z. Substituting the expressions for revenue and cost of local bilateral transaction into equation (5.1), gives following equation for return of local bilateral transaction, r_{lb},

$$r_{lb}=\frac{\sum_{z=1}^{Z} p_{lb,z}\pi_{lb,z}}{\sum_{z=1}^{Z}\left(a_g\left(p_{lb,z}\right)^2+b_g p_{lb,z}+c_g\right)}-1 \tag{6.10}$$

Equation (6.10) is a general expression for return of local bilateral transaction over a total of Z trading intervals. GenCo g's optimal allocation of power quantity to each trading option will be determined as a result of portfolio optimization. Note, a GenCo will not be over committed because portfolio optimization constrains total power allocations of GenCo to its *Capacity*. Before carrying out portfolio optimization, GenCo g is interested in exploring the possibility of allocating maximum feasible power quantity to local Financial Bilateral Transaction, $p_{lb,\max}^{FBT}$, in all trading intervals. Therefore, substituting $p_{lb,z}$ with $p_{lb,\max}^{FBT}$ in equation (6.10) yields,

$$r_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,\max}^{FBT} \pi_{lb,z}}{\sum_{z=1}^{Z} \left(a_g \left(p_{lb,\max}^{FBT} \right)^2 + b_g \, p_{lb,\max}^{FBT} + c_g \right)} - 1 \tag{6.11}$$

Moreover, in this model a local bilateral transaction has same price, π_{lb}, irrespective of trading interval z. Therefore, substituting price of local bilateral transaction in trading interval z, $\pi_{lb,z}$, with π_{lb} in equation (6.11) leads to,

$$r_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,\max}^{FBT} \pi_{lb}}{\sum_{z=1}^{Z} \left(a_g \left(p_{lb,\max}^{FBT} \right)^2 + b_g \, p_{lb,\max}^{FBT} + c_g \right)} - 1 \tag{6.12}$$

where (6.12) is applicable to the basic as well as the improved model of portfolio optimization over a total of Z trading intervals. In equation (6.12), a_g , b_g , c_g and π_{lb} are assumed certain at the time of portfolio optimization. Moreover, local bilateral transaction does not carry transmission congestion risk because it does not use transmission network. Consequently, actual return of local bilateral transaction is the same as its expected return, $E(r_{lb}) = r_{lb}$.

Risk-free Non-local Financial Bilateral Transactions

Revenue from non-local bilateral transaction with LSE at node i is calculated as $\sum_{z=1}^{Z} p_{i,z} \pi_{i,z}$, where $p_{i,z}$ is power quantity and $\pi_{i,z}$ is energy price for non-local bilateral transaction in trading interval z. Total cost of non-local bilateral transaction with LSE at node i depends on power quantity $p_{i,z}$ in each trading interval z, and from

(6.9) can be calculated as $\sum_{z=1}^{Z}\left(a_g\left(p_{i,z}\right)^2+b_g p_{i,z}+c_g\right)$. Substituting the expressions for revenue and cost of the non-local bilateral transaction in equation (5.1) yields following expression for return of non-local bilateral transaction with LSE at node *i*, r_i,

$$r_i=\frac{\sum_{z=1}^{Z}p_{i,z}\pi_{i,z}}{\sum_{z=1}^{Z}\left(a_g\left(p_{i,z}\right)^2+b_g p_{i,z}+c_g\right)}-1 \tag{6.13}$$

Equation (6.13) is a general expression for decision period return for non-local bilateral transaction with LSE at node *i* over a total of *Z* trading intervals. GenCo *g* is interested in exploring the possibility of allocating maximum feasible power quantity allocation to the non-local Financial Bilateral Transaction, $p_{i,\max}^{FBT}$, in all trading intervals. Therefore, substituting $p_{i,z}$ with $p_{i,\max}^{FBT}$ in equation (6.13) leads to,

$$r_i=\frac{\sum_{z=1}^{Z}p_{i,\max}^{FBT}\pi_{i,z}}{\sum_{z=1}^{Z}\left(a_g\left(p_{i,\max}^{FBT}\right)^2+b_g p_{i,\max}^{FBT}+c_g\right)}-1 \tag{6.14}$$

Similar to local bilateral transaction, a non-local bilateral transaction with LSE at node *i* has same price, π_i, irrespective of trading interval *z*. Therefore, substituting price of non-local bilateral transaction with LSE at node *i* in trading interval *z*, $\pi_{i,z}$ with π_i in equation (6.14) gives,

$$r_i=\frac{\sum_{z=1}^{Z}p_{i,\max}^{FBT}\pi_{i}}{\sum_{z=1}^{Z}\left(a_g\left(p_{i,\max}^{FBT}\right)^2+b_g p_{i,\max}^{FBT}+c_g\right)}-1 \tag{6.15}$$

The above expression (6.15) applies to both basic and improved models of portfolio optimization over a total of *Z* trading intervals. As before, a_g, b_g, c_g and $\pi_{i,z}$ in equation (6.15) are assumed certain at the time of portfolio optimization. Moreover, non-local bilateral transaction does not carry transmission congestion risk because it is assumed here that GenCo is not responsible for transmission congestion charges. For simplicity, the modelling of transmission congestion charges is not shown here for GenCo, however, in section 6.3 of this chapter, it is shown how transmission congestion charges are included in modelling for LSE. If GenCo are to be responsible for part of the transmission congestion charges, equations (6.14) can be similarly modified.

Since here non-local bilateral transactions are risk-free, their actual returns are the same as their expected returns, i.e. $E(r_i) = r_i$ for $i = 1, \cdots, N, i \neq ln$.

Day-ahead auction

Decision period revenue of a GenCo from day-ahead auction is calculated as $\sum_{z=1}^{Z} p_{ln,z} \lambda_{ln,z}$, where $p_{ln,z}$ and $\lambda_{ln,z}$ represent unknown power quantity and price (that will be scheduled and cleared by ISO) in trading interval *z* at local node (*ln*). Similarly as before, cost of day-ahead auction over all trading intervals is calculated from (6.9) as $\sum_{z=1}^{Z} \left(a_g \left(p_{ln,z} \right)^2 + b_g p_{ln,z} + c_g \right)$. Substituting the expressions for revenue and cost of day-ahead auction in equation (5.1) gives the following return of day-ahead auction, r_{daa},

$$r_{daa} = \frac{\sum_{z=1}^{Z} p_{ln,z} \lambda_{ln,z}}{\sum_{z=1}^{Z} \left(a_g \left(p_{ln,z} \right)^2 + b_g p_{ln,z} + c_g \right)} - 1 \qquad (6.16)$$

Equation (6.16) is a general expression for return of day-ahead auction over a total of *Z* trading intervals. Although GenCo *g* does not know $p_{ln,z}$, the power quantity that will be scheduled by ISO in trading interval *z*, it is interested in exploring the possibility of allocating maximum feasible power quantity allocation to the day-ahead auction, $p_{ln,\max}^{DAA}$, in all trading intervals. Therefore, return for the day-ahead auction, r_{daa}, is obtained by substituting $p_{ln,z}$ with $p_{ln,\max}^{DAA}$ in (6.16), so that,

$$r_{daa} = \frac{\sum_{z=1}^{Z} p_{ln,\max}^{DAA} \lambda_{ln,z}}{\sum_{z=1}^{Z} \left(a_g \left(p_{ln,\max}^{DAA} \right)^2 + b_g p_{ln,\max}^{DAA} + c_g \right)} - 1 \tag{6.17}$$

Equation (6.17) is applicable to both basic and improved models of portfolio optimization over a total of Z trading intervals. Again, a_g, b_g and c_g are assumed certain in (6.17), at the time of portfolio optimization, however, value of $\lambda_{ln,z}$ is uncertain because $\lambda_{ln,z}$ represents LMP at local node in interval *z*. Note that the values of these LMPs can vary between trading intervals.

In this thesis, portfolio optimization considers overall variations of LMPs at system nodes in all trading intervals of the decision period. However, it does not consider variations in LMPs at the same node between trading intervals that have different time-of-day or time-of-year characteristics, as explained next. According to time-of-year, a trading interval may be defined as a winter or summer interval but seasonal variations are not modelled in FABS. Similarly, in terms of time-of-day, a trading interval can be defined as a peak or an off-peak interval but our portfolio optimization model gives the same solution for all trading intervals in the decision period. Due to uncertain values of $\lambda_{ln,z}$ in trading intervals of the decision period in future, λ_{ln} is defined as a random variable to represent overall variable LMP, irrespective of trading interval, at local node *ln*. Substituting λ_{ln} for $\lambda_{ln,z}$ in (6.17) yields,

$$r_{daa} = \frac{p_{ln,\max}^{DAA} \times Z \times \lambda_{ln}}{\sum_{z=1}^{Z} \left(a_g \left(p_{ln,\max}^{DAA} \right)^2 + b_g p_{ln,\max}^{DAA} + c_g \right)} - 1 \tag{6.18}$$

Due to the uncertainty associated with random variable λ_{ln}, expected return for the day-ahead auction is not the same as return of day-ahead auction represented by (6.18). Expectation of the return, $E(r_{daa})$, depends on expectation of LMP at local node, $E\left(\lambda_{ln}\right)$. Substituting $E\left(\lambda_{ln}\right)$ for λ_{ln} and $E(r_{daa})$ for r_{daa} in (6.18) leads to,

$$E_{daa} = E(r_{daa}) = \frac{p_{ln,\max}^{DAA} \times Z \times E\left(\lambda_{ln}\right)}{\sum_{z=1}^{Z}\left(a_g\left(p_{ln,\max}^{DAA}\right)^2 + b_g p_{ln,\max}^{DAA} + c_g\right)} - 1 \qquad (6.19)$$

Equation (6.19) shows that GenCo's expected return for day-ahead auction, $E(r_{daa})$, is directly proportional to overall expectation of LMP at local node, $E(\lambda_{ln})$, during the decision period.

A GenCo needs to evaluate its expected return for each trading option, as explained above. The expected returns count towards the "return" aspect in the risk-return trade-off evaluated by portfolio optimization, as discussed in introduction of this Chapter.

6.2.3.2 Variances of Returns for Trading Options

In addition to evaluating the "return" aspect in the risk-return trade-off, GenCo needs to evaluate the "risk" aspect. The risk evaluation involves calculation of variance in return of each trading option as well as covariance between returns of all trading options. Equations for variance in return of each trading option are developed as follows.

Risk-free Non-local and Local Financial Bilateral Transactions

Since returns of all bilateral transactions of a GenCo are constant and variance of a constant is zero, variance of return for all bilateral transactions is set to zero,

$$\sigma^2(r_i) = 0$$
$$i = 1, \cdots, N \qquad (6.20)$$

Risky Day-ahead Auction

As shown in equation (6.19), random variable of LMP at local node, λ_{ln}, introduces uncertainty in return of day-ahead auction. Consequently, day-ahead auction is a risky trading option that requires a risk assessment. Variance is a measure of risk that can be used for the risk analysis. Equation (6.19) is a function of a random variable and variance has following property for functions of random variables,

$$Var\left(a+bX\right)=b^{2}Var\left(X\right) \tag{6.21}$$

where *a* and *b* are constants and *X* is a random variable. Applying the property of variance (6.21) to equation (6.19) leads to following expression for variance of return for day-ahead auction, $\sigma^{2}(r_{daa})$,

$$\sigma_{daa}^{2}=\sigma^{2}(r_{daa})=\left(\frac{p_{ln,\max}^{DAA}\times Z}{\sum_{z=1}^{Z}\left(a_{g}\left(p_{ln,\max}^{DAA}\right)^{2}+b_{g}p_{ln,\max}^{DAA}+c_{g}\right)}\right)^{2}\sigma^{2}(\lambda_{ln}) \tag{6.22}$$

6.2.3.3 Covariance between Returns from Trading Options

In addition to variance of each return, covariance between returns of all trading options can also contribute to risk. Therefore risk evaluation must explore covariance between returns of all trading options, as discussed next.

Covariance between Returns of Risk-free Local Financial Bilateral Transaction and Risk-free Non-local Financial Bilateral Transaction

Since return of local bilateral transaction of a GenCo is a constant and covariance between a constant and another constant/variable is zero, covariance between return of a local bilateral (*lb*) and return of any non-local bilateral transaction is zero,

$$\begin{gathered}\sigma(r_{lb},r_{i})=0\\ i=1,\cdots,N,i\neq ln\end{gathered} \tag{6.23}$$

Covariance between Returns of Risk-free Local Financial Bilateral Transaction and Risky Day-ahead Auction

Since return of local bilateral transaction of a GenCo is a constant and covariance between a constant and another constant/variable is zero, covariance between return of local bilateral transaction and return of day-ahead auction is zero,

$$\sigma(r_{lb}, r_{daa}) = 0 \tag{6.24}$$

Covariance between Returns of a Risk-free Non-local Financial Bilateral Transaction and another Risk-free Non-local Financial Bilateral Transaction

Since return of a non-local bilateral transaction of a GenCo is a constant and covariance between a constant and another constant/variable is zero, covariance between returns of two non-local bilateral transactions is zero,

$$\begin{gathered} \sigma(r_i, r_j) = 0 \\ i = 1, \cdots, N, i \neq ln,\ j = 1, \cdots, N,\ j \neq ln,\ j \neq i \end{gathered} \tag{6.25}$$

Covariance between Returns of a Risk-free Non-local Financial Bilateral Transaction and Risky Day-ahead Auction

Since return of a non-local bilateral transaction of a GenCo is a constant and covariance between a constant and another constant/variable is zero, covariance between return of a non-local bilateral transaction and return of day-ahead auction is zero,

$$\begin{gathered} \sigma(r_i, r_{daa}) = 0 \\ i = 1, \cdots, N, i \neq ln \end{gathered} \tag{6.26}$$

6.2.4 Objective or Utility Function of Portfolio Optimization

For GenCo *g*, overall expected return, $E(r_g)$, is sum of its expected returns from *N*+1 trading options, expressed as,

$$E(r_g) = \sum_{\tau=1}^{N+1} x_\tau E_\tau \tag{6.27}$$

where τ is a trading option out of total *N*+1 trading options, x_τ is decision variable for power allocation fraction of *Capacity* to trading option τ and E_τ is expected return for trading option τ.

The GenCo's overall variance of return, $\sigma^2(r_g)$, is expressed by sum of its variances and covariances of returns from *N*+1 trading options, as follows,

$$\sigma^2(r_g) = \sum_{\tau=1}^{N+1} x_\tau^2 \sigma_\tau^2 + \sum_{\tau=1}^{N+1} \sum_{\substack{\tau'=1 \\ \tau' \neq \tau}}^{N+1} x_\tau x_{\tau'} \sigma_{\tau,\tau'} \tag{6.28}$$

where τ is a trading option out of total *N*+1 trading options, τ' is another trading option (different from τ, i.e. $\tau' \neq \tau$) out of total *N*+1 trading options, power allocation fractions of *Capacity* for trading option τ and τ' are denoted by decision variables x_τ and $x_{\tau'}$ respectively, σ_τ^2 is variance of return for trading option τ and $\sigma_{\tau,\tau'}$ is covariance between returns of trading options τ and τ'.

Substituting expression of overall expectation from (6.27) and variance from (6.28) into overall utility function (5.32) leads to,

$$U_g = \sum_{\tau=1}^{N+1} x_\tau E_\tau - \frac{1}{2} A \left\{ \sum_{\tau=1}^{N+1} x_\tau^2 \sigma_\tau^2 + \sum_{\tau=1}^{N+1} \sum_{\substack{\tau'=1 \\ \tau' \neq \tau}}^{N+1} x_\tau x_{\tau'} \sigma_{\tau,\tau'} \right\} \tag{6.29}$$

where U_g is GenCo *g*'s overall utility of portfolio optimization and *A* is risk aversion factor that shows how strongly the GenCo wants to avoid risk.

6.2.5 Optimal Portfolio of Trading Options

A GenCo can obtain its optimal portfolio, i.e. optimal power allocation fractions of *Capacity* to trading options, by maximizing the utility function (6.29) as follows,

$$\text{Maximize}_{x_\tau, x_{\tau'}} \; U_g = \sum_{\tau=1}^{N+1} x_\tau E_\tau - \frac{1}{2} A \left\{ \sum_{\tau=1}^{N+1} x_\tau^2 \sigma_\tau^2 + \sum_{\tau=1}^{N+1} \sum_{\substack{\tau'=1 \\ \tau' \neq \tau}}^{N+1} x_\tau x_{\tau'} \sigma_{\tau,\tau'} \right\} \tag{6.30}$$

subject to

$$\begin{aligned} &\sum_{\tau=1}^{N+1} x_\tau = 1 \\ &0 \le x_\tau \le x_{\tau,max} \end{aligned} \tag{6.31}$$

where x_τ represents power allocation fraction of *Capacity* to trading option τ, out of total *N*+1 trading options, and $x_{\tau,max}$ denotes upper limit on power allocation fraction to trading option τ.

The optimization problem (6.30)-(6.31) can be solved by any standard non-linear programming solver. Matlab function for constrained non-linear programming, *fmincon*, is used to solve the optimization problem in this thesis.

6.2.6 Optimal Power Quantity Allocations to Trading Options

Optimal power allocation fractions of a GenCo's *Capacity* are used to calculate optimal power quantities allocated to trading options. The calculation methods for risky day-ahead auction as well as risk-free local and non-local Financial Bilateral Transactions are described next.

6.2.6.1 Risky day-ahead auction

Optimal power allocation fraction to the day-ahead auction, $x_{ln,opt}^{DAA}$, determines optimal power quantity allocation to risky day-ahead auction, $p_{ln,opt}^{DAA}$, as,

$$p_{ln,opt}^{DAA} = x_{ln,opt}^{DAA} \times p_g^{\max} \qquad (6.32)$$

6.2.6.2 Risk-free non-local Financial Bilateral Transactions

Optimal power quantity allocation to the risky non-local Financial Bilateral Transaction, $p_{i,opt}^{FBT}$, depends on optimal power allocation fraction to bilateral transaction with LSE at node *i*, $x_{i,opt}^{FBT}$,

$$p_{i,opt}^{FBT} = x_{i,opt}^{FBT} \times p_g^{\max} \qquad (6.33)$$

6.2.6.3 A risk-free local Financial Bilateral Transaction

Optimal power allocation fraction to risk-free local bilateral (*lb*) transaction, $x_{lb,opt}^{FBT}$, determines optimal power quantity allocation to the local bilateral (*lb*) transaction, $p_{lb,opt}^{FBT}$, as,

$$p_{lb,opt}^{FBT} = x_{lb,opt}^{FBT} \times p_g^{\max} \qquad (6.34)$$

6.3 Portfolio Optimization Procedure of a Generation Company

As mentioned earlier, energy prices in day-ahead markets serve as reference prices for financial bilateral negotiations in electricity markets of USA [4]. Each GenCo needs to do statistical analysis of LMPs (by formulae presented in Chapter 5) in the previous year before portfolio optimization for the next year. GenCo is not responsible for transmission congestion charges because it sells energy to LSEs at its local node. Therefore, a GenCo sets overall expectation of LMP at local node $E(\lambda_{ln})$ as assumed prices for all bilateral transactions. Portfolio optimization procedure of a Generation Company consists of following steps.

1. If using **Basic Portfolio Optimization Procedure** then compute maximum feasible power quantity allocations to trading options by equations (6.1), (6.2) and (6.4).
2. If using **Improved Portfolio Optimization Procedure** then compute maximum feasible power quantity allocations to trading options by equations (6.1), (6.3) and (6.5).
3. Compute upper limits of decision variables for power allocations to trading options by equations (6.6), (6.7) and (6.8).
4. Compute expected return for all trading options by equations (6.12), (6.15) and (6.19).
5. Compute variance of return for all trading options by equations (6.20) and (6.22).
6. Compute covariance of return for all trading options by equations (6.23)-(6.26).
7. Solve portfolio optimization problem defined by (6.30)-(6.31).
8. Compute optimal power quantity allocations to trading options by equations (6.32), (6.33) and (6.34).

6.4 Basic and Improved Models of Portfolio Optimization for a Load Serving Entity

Permanent minimum load requirement of an LSE (during all hours) is called its *Base Load*. Base load of LSE l, p_l^{base}, can be met through a number of trading options. In order to develop generic basic and improved portfolio optimization models, it is decided to consider as many bilateral transaction options as the number of nodes, N, in a power system. The generic basic and improved models are valid irrespective of the number or location of GenCos in the power system. Both models assume that a maximum of one GenCos is connected to any node of the power system. However, the models can also accommodate a single node with two GenCos and any number of nodes without GenCos. In addition, the options to trade by submitting price-sensitive demand bids and price-inelastic load demands in day-ahead auction is included in the generic models. As a result, both generic portfolio optimization models consider a total of N+1 trading options.

Portfolio optimization of an LSE determines optimal allocation of its *Base Load* among N+1 trading options. Decision or unknown variables of portfolio optimization by LSE l are the fractions of its *Base Load*, p_l^{base}, allocated to N+1 trading options. In order to solve its portfolio optimization problem, an LSE must assume energy prices of its trading options and know upper limits of its decision variables. To find the upper limits of decision variables, however, an LSE first needs to determine maximum feasible power quantity allocations for all trading options. The maximum feasible power quantity allocations are also required to evaluate the expectation, variance and covariance of return (collectively termed return characteristics) for trading options.

Calculation methods for maximum feasible power quantity allocations, upper limits of decision variables and return characteristics of all trading options are covered in Sections 6.4.1, 6.4.2 and 6.4.3 respectively.

6.4.1 Maximum Feasible Power Quantity Allocations to Trading Options

Direct-search Financial Bilateral Transactions of an LSE can be divided into two types: (i) bilateral transaction with GenCo at local node and (ii) bilateral transactions with GenCos at non-local nodes. LSEs' non-local Financial Bilateral Transactions are risky because LSEs are responsible for transmission congestion costs. However, local Financial Bilateral Transactions of LSEs are risk-free because they do not use transmission network. The two types of an LSE's direct-search Financial Bilateral Transactions are termed risky non-local and risk-free local Financial Bilateral Transactions respectively.

In addition to these two types of Financial Bilateral Transactions, an LSE can trade energy by submitting price-sensitive demand bids and price-inelastic load demands in day-ahead auction. Price-sensitive demand bids are submitted by LSEs and processed by ISO to determine which ones are most competitive (highest priced) and should be allowed. Price-sensitive demand bids of an LSE represent its willingness to buy specified power quantities if it can get energy prices that are lower or equal to its specified energy prices. An LSE's participation in day-ahead energy auction is a risky option because market prices can fluctuate unpredictably and it has to compete with other LSEs in the market. ISO will not accept price-sensitive demand bids of an LSE if it finds that energy prices offered by other LSEs are higher and thus more competitive.

Discussion of maximum feasible power quantity allocations for risky day-ahead auction is covered in Section 6.4.1.1. If a bilateral transaction option is infeasible due to absence of any GenCo at a particular node then maximum feasible power quantity allocation of the trading option is set to zero. Otherwise, maximum feasible power quantity allocations for risky non-local and risk-free local Financial Bilateral Transaction options are determined as discussed in Section 6.4.1.2 and Section 6.4.1.3 respectively.

6.4.1.1 Risky day-ahead auction

If an LSE cannot secure a bilateral transaction then it has an option to bid for its *Base Load*, p_l^{base}, in day-ahead auction. In both basic and improved portfolio optimization models, maximum feasible power quantity allocation for the day-ahead auction, $p_{ln,\max}^{DAA}$, is set as,

$$p_{ln,\max}^{DAA} = p_l^{base} \tag{6.35}$$

6.4.1.2 Risky non-local Financial Bilateral Transactions

The basic model ignores maximum quantities of simultaneously feasible Financial Bilateral Transactions announced by ISO for LSE *l*. It assumes that LSE *l*'s *Base Load*, p_l^{base}, can be allocated to a non-local Financial Bilateral Transaction. In consequence, maximum feasible power quantity allocation to non-local transaction with GenCo at node *i*, $p_{i,\max}^{FBT}$, is set as follows,

$$p_{i,\max}^{FBT} = p_l^{base} \tag{6.36}$$

However, the assumption of basic model is not valid for practical power systems, as ISO can reduce non-local bilateral transactions if they are not simultaneously feasible. These reductions are loss of bilateral transaction opportunity for market participants. If LSE had adhered to simultaneous feasibility constraints announced by ISO then it could have allocated lost opportunity fraction of its *Base Load* to alternative bilateral transaction options. Thus it is crucial to improve the basic portfolio optimization model of an LSE to avoid the reductions by ISO and the consequent opportunity losses to LSEs.

The improved model considers maximum quantities of simultaneously feasible Financial Bilateral Transactions announced by ISO for an LSE. This quantity is used as maximum quantity of LSE's feasible Financial Bilateral Transaction, publicly announced by ISO, with GenCo at node *i*, denoted as $p_{i,\max}^{SFT}$. The maximum feasible power quantity allocation for non-local transaction, privately determined by LSE, with GenCo at node *i* is denoted as $p_{i,\max}^{FBT}$. An LSE determines its $p_{i,\max}^{FBT}$ by considering $p_{i,\max}^{SFT}$ as shown in following equation,

$$p_{i,\max}^{FBT} = \begin{cases} p_l^{base}, & p_l^{base} < p_{i,\max}^{SFT} \\ p_{i,\max}^{SFT}, & p_l^{base} > p_{i,\max}^{SFT} \end{cases} \tag{6.37}$$

6.4.1.3 A risk-free local Financial Bilateral Transaction

The basic model ignores generation capability reported to LSE *l* by its local GenCo *g*, p_g^{local}, and assumes that local GenCo can meet LSE *l*'s *Base Load*, p_l^{base}. In basic model, maximum feasible power quantity allocation to the local bilateral (*lb*) transaction, $p_{lb,\max}^{FBT}$, is set as,

$$p_{lb,\max}^{FBT} = p_l^{base} \tag{6.38}$$

In practical power systems, if generation capability of local GenCo g, p_g^{local}, is less than LSE l's *Base Load*, p_l^{base}, then assumption of basic model will not hold. In such case, if LSE allocates p_l^{base} to local transaction then it will face loss of opportunity. If LSE had considered generation capability reported by local GenCo g, p_g^{local}, then it could have allocated lost opportunity fraction of its *Base Load* to alternative trading options. Therefore, the basic portfolio optimization model of an LSE must be improved for local bilateral transaction to avoid the loss of opportunity.

The improved model considers generation capability reported to LSE l by its local GenCo g, p_g^{local}. As a result, maximum feasible power quantity allocation for the local bilateral transaction, $p_{lb,\max}^{FBT}$, may be limited by p_g^{local} and can be determined as,

$$p_{lb,\max}^{FBT} = \begin{cases} p_l^{base}, & p_l^{base} < p_g^{local} \\ p_g^{local}, & p_l^{base} > p_g^{local} \end{cases} \tag{6.39}$$

6.4.2 Upper limits of Decision Variables for Power Allocations to Trading Options

Once maximum feasible power quantity allocations are known for all trading options, it becomes possible to determine upper limits of decision variables for power allocations to the trading options. Decision or unknown variables of LSE l are the power allocation fractions of its *Base Load*, p_l^{base}, allocated to N+1 trading options. For both basic and improved models, methods of determining upper limits of power allocation fractions of *Base Load* for trading options are the same. These methods for risky day-ahead auction, risk-free non-local Financial Bilateral Transactions and risk-free local Financial Bilateral Transactions are discussed next.

6.4.2.1 Risky day-ahead auction

Upper limit of power allocation fraction of LSE l's *Base Load*, p_l^{base}, for risky day-ahead auction, $x_{ln,\max}^{DAA}$, depends on value of maximum feasible power quantity allocation to the day-ahead auction, $p_{ln,\max}^{DAA}$. The upper limit is set as,

$$x_{ln,\max}^{DAA} = p_{ln,\max}^{DAA} \big/ p_l^{base} \tag{6.40}$$

6.4.2.2 Risky non-local Financial Bilateral Transactions

Maximum feasible power quantity allocation to risky non-local Financial Bilateral Transaction with GenCo at node i, $p_{i,\max}^{FBT}$, determines upper limit of power allocation fraction of LSE l's *Base Load*, p_l^{base}, to the bilateral transaction, $x_{i,\max}^{FBT}$,

$$x_{i,\max}^{FBT} = p_{i,\max}^{FBT} \big/ p_l^{base} \tag{6.41}$$

6.4.2.3 A risk-free local Financial Bilateral Transaction

Upper limit of power allocation fraction of LSE l's *Base Load*, p_l^{base}, for risk-free local bilateral (*lb*) transaction, $x_{lb,\max}^{FBT}$, depends on value of maximum feasible power quantity allocation to the bilateral transaction, $p_{lb,\max}^{FBT}$. The upper limit is set as,

$$x_{lb,\max}^{FBT} = p_{lb,\max}^{FBT} \big/ p_l^{base} \tag{6.42}$$

6.4.3 Return Characteristics of Trading Options

Return characteristics include expectation, E, variance, σ^2, and covariance, σ, of return for all trading options. For determining the statistical return characteristics, an LSE needs to do statistical analysis of LMPs in the previous year, which involves determination of expectation, E, variance, σ^2, and covariance, σ, of LMPs, as shown in Chapter 5. For determining the return characteristics, an LSE also needs to calculate maximum feasible power quantity allocations to all trading options, by formulae presented in Section 6.4.1. The return characteristics of day-ahead auction and risk-free local bilateral transaction are determined in the same way for both models. However, the return characteristics of risky non-local bilateral transaction are determined in different ways, as described next.

6.4.3.1 Returns and Expected Returns for Trading Options

Every LSE carries out its portfolio optimization for a specified decision period. The decision period can be a month, a year or any other length of time. A trading option's rate of return, in short return, is its benefit-to-cost ratio that is a measure of its financial performance. Benefit of a trading option is determined by the difference between its revenue and cost. In this section, revenue, cost and return refer to a specific trading option of an LSE over a specified decision period. Return is defined by equation (5.1) that is used to develop expressions of returns for all trading options of an LSE, as shown next.

Risk-free Local Financial Bilateral Transaction

Assuming that decision period has a total of *Z* trading intervals, cost of local bilateral transaction with GenCo at local node over all trading intervals is calculated as $\sum_{z=1}^{Z} p_{lb,z}\pi_{lb,z}$, where $p_{lb,z}$ is power quantity and $\pi_{lb,z}$ is energy price for local bilateral (*lb*) transaction in trading interval *z*. Total revenue from end-consumers served by LSE, with energy obtained from local bilateral transaction, is calculated as $\sum_{z=1}^{Z} p_{lb,z}\gamma_{ln}$ where γ_{ln} is flat-rate agreed with the end-consumers at local node (*ln*). Substituting the expressions for revenue and cost of local bilateral transaction in (5.1), gives following equation for return of local bilateral transaction, r_{lb},

$$r_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,z}\gamma_{ln}}{\sum_{z=1}^{Z} p_{lb,z}\pi_{lb,z}} - 1 \qquad (6.43)$$

Equation (6.43) is a general expression for return of local bilateral transaction over a total of Z trading intervals. LSE l's optimal allocation of power quantity to each trading option will be determined as a result of portfolio optimization. Note that an LSE will not be over committed because portfolio optimization constrains total power allocations of LSE to its *Base Load.* Before carrying out portfolio optimization, LSE *l g* is interested in exploring the possibility of allocating maximum feasible power quantity to local Financial Bilateral Transaction, $p_{lb,\max}^{FBT}$, in all trading intervals. Therefore, substituting $p_{lb,z}$ with $p_{lb,\max}^{FBT}$ in equation (6.43) yields,

$$r_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,\max}^{FBT} \gamma_{ln}}{\sum_{z=1}^{Z} p_{lb,\max}^{FBT} \pi_{lb,z}} - 1 \qquad (6.44)$$

Moreover, in this model a local bilateral transaction has same price, π_{lb}, irrespective of trading interval z. Therefore, substituting $\pi_{lb,z}$ with π_{lb} in equation (6.44) leads to,

$$r_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,\max}^{FBT} \gamma_{ln}}{\sum_{z=1}^{Z} p_{lb,\max}^{FBT} \pi_{lb}} - 1 \qquad (6.45)$$

where (6.45) is applicable to both basic and improved models of portfolio optimization over a total of Z trading intervals. In equation (6.45), γ_{ln} and π_{lb} are assumed certain at the time of portfolio optimization. Moreover, local bilateral transaction does not carry transmission congestion risk because it does not use transmission network. Consequently, actual return of local bilateral transaction is the same as its expected return, $E(r_{lb}) = r_{lb}$.

Risky Non-local Financial Bilateral Transactions

Cost of non-local bilateral transaction with GenCo at node i, over all trading intervals, is calculated as $\sum_{z=1}^{Z} p_{i,z}\pi_{i,z}$, where $p_{i,z}$ is power quantity and $\pi_{i,z}$ is energy price for the non-local bilateral transaction in trading interval z. An LSE's income from end-consumers, served by LSE at its local node, contributes to its revenue. However, revenue of LSE is not the same as its income because of transmission congestion charges, over all trading intervals. Furthermore, if an LSE holds Financial Transmission Rights (FTRs) then FTR credits from ISO can reduce LSE's transmission congestion charges. As a result, revenue of LSE over all trading intervals depends on (i) income from end-consumers, (ii) transmission congestion charges and (iii) FTR credits. LSE's revenue from a non-local bilateral transaction is given by,

$$Revenue = Income - Congestion\ Charges + FTR\ Credits \qquad (6.46)$$

An LSE's total income from end-consumers served by LSE, with energy obtained from non-local bilateral transaction with GenCo at node i, is calculated as,

$$\sum_{z=1}^{Z} p_{i,z}\gamma_{ln} \qquad (6.47)$$

where γ_{ln} is flat-rate agreed with the end-consumers at local node (ln). Total transmission congestion charges are expressed as,

$$\sum_{z=1}^{Z} p_{i,z}\left(\lambda_{ln,z} - \lambda_{i,z}\right) \qquad (6.48)$$

where $\lambda_{ln,z}$ and $\lambda_{i,z}$ are LMPs, in trading interval z, at local node (ln) and node i respectively.

If LSE holds Financial Transmission Rights (FTRs) between its local node (ln) and GenCo node i, $FTR_i^{held,quantity}$, then FTR credit payments from ISO are,

$$\sum_{z=1}^{Z} FTR_i^{held,quantity}\left(\lambda_{ln,z} - \lambda_{i,z}\right) \qquad (6.49)$$

Substituting formulae for income from end-consumers (6.47), transmission congestion charges (6.48) and FTR credits (6.49) into equation (6.46) yields following expression for revenue from non-local bilateral transaction with GenCo at node *i*,

$$\sum_{z=1}^{Z} p_{i,z}\gamma_{ln} - \sum_{z=1}^{Z} p_{i,z}\left(\lambda_{ln,z} - \lambda_{i,z}\right) + \sum_{z=1}^{Z} FTR_i^{held,quantity}\left(\lambda_{ln,z} - \lambda_{i,z}\right) \qquad (6.50)$$

Substituting the expressions for revenue and cost of local bilateral transaction in (5.1), gives following equation for return of non-local bilateral transaction with GenCo at node *i*, r_i,

$$r_i = \frac{\sum_{z=1}^{Z} p_{i,z}\gamma_{ln} - \sum_{z=1}^{Z} p_{i,z}\left(\lambda_{ln,z} - \lambda_{i,z}\right) + \sum_{z=1}^{Z} FTR_i^{held,quantity}\left(\lambda_{ln,z} - \lambda_{i,z}\right)}{\sum_{z=1}^{Z} p_{i,z}\pi_{i,z}} - 1 \qquad (6.51)$$

Equation (6.51) is a general expression of return for non-local bilateral transaction with GenCo at node *i* over a total of *Z* trading intervals. LSE *l* is interested in exploring the possibility of allocating maximum feasible power quantity allocation to the non-local Financial Bilateral Transaction, $p_{i,\max}^{FBT}$, for all trading intervals. Therefore, substituting $p_{i,z}$ with $p_{i,\max}^{FBT}$ in equation (6.51) and combining terms containing $\left(\lambda_{ln,z} - \lambda_{i,z}\right)$ leads to,

$$r_i = \frac{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\gamma_{ln} - \sum_{z=1}^{Z}\left(p_{i,\max}^{FBT} - FTR_i^{held,quantity}\right)\left(\lambda_{ln,z} - \lambda_{i,z}\right)}{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\pi_{i,z}} - 1 \qquad (6.52)$$

Similar to local bilateral transaction, a non-local bilateral transaction with GenCo at node *i* has same price, π_i, irrespective of trading interval *z*. Therefore, substituting $\pi_{i,z}$ with π_i in equation (6.52) and rearranging the numerator gives,

$$r_i = \frac{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\gamma_{ln} - \left(p_{i,\max}^{FBT} - FTR_i^{held,quantity}\right)\left\{\sum_{z=1}^{Z}\lambda_{ln,z} - \sum_{z=1}^{Z}\lambda_{i,z}\right\}}{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\pi_i} - 1 \qquad (6.53)$$

Equation (6.53) is applicable over a total of Z trading intervals. At the time of portfolio optimization, γ_{ln} and $FTR_i^{held,quantity}$ is assumed certain in this equation. However, values of $\lambda_{ln,z}$ and $\lambda_{i,z}$ are uncertain because they represent LMPs, in interval z, at local node (ln) and GenCo node i respectively. Note that the values of both LMPs can vary between trading intervals.

In this thesis, portfolio optimization considers overall variations of LMPs at system nodes in all trading intervals of the decision period. However, it does not consider variations in LMPs at the same node between trading intervals that have different time-of-day or time-of-year characteristics, as explained next. According to time-of-year, a trading interval may be defined as a winter or summer interval but seasonal variations are not modelled in FABS. Similarly, in terms of time-of-day, a trading interval can be defined as a peak or an off-peak interval but our portfolio optimization model gives the same solution for all trading intervals in the decision period. Due to uncertain values of $\lambda_{ln,z}$ ($\lambda_{i,z}$) in trading intervals of the decision period in future, λ_{ln} ($\lambda_{i,z}$) is defined as a random variable to represent overall variable LMP, irrespective of trading interval, at local node ln (node i). Substituting λ_{ln} and λ_i, for $\lambda_{ln,z}$ and $\lambda_{i,z}$ in (6.53) yields,

$$r_i = \frac{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\gamma_{ln} - \left\{\begin{matrix}\left(p_{i,\max}^{FBT} - FTR_i^{held,quantity}\right) \\ \times\left(Z\times\lambda_{ln} - Z\times\lambda_i\right)\end{matrix}\right\}}{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\pi_i} - 1 \qquad (6.54)$$

Due to the uncertainty of random variables λ_{ln} and λ_i, expected return for the non-local bilateral transaction is not the same as return of non-local bilateral transaction represented by (6.54). Expectation of the return, $E(r_i)$, depends on expectation of

LMP at local node, $E(\lambda_{ln})$, and node *i*, $E(\lambda_i)$. Substituting $E(\lambda_{ln})$ and $E(\lambda_i)$ for λ_{ln} and λ_i in (6.54) leads to,

$$E_i = E(r_i) = \frac{\sum_{z=1}^{Z} p_{i,\max}^{FBT} \gamma_{ln} - \left\{ \begin{matrix} \left(p_{i,\max}^{FBT} - FTR_i^{held,quantity} \right) \\ \times Z \left(E(\lambda_{ln}) - E(\lambda_i) \right) \end{matrix} \right\}}{\sum_{z=1}^{Z} p_{i,\max}^{FBT} \pi_i} - 1 \tag{6.55}$$

$$i = 1, \cdots, N, i \neq ln$$

Expression (6.55) is valid for both basic and improved models of portfolio optimization but $FTR_i^{held,quantity}$ is set to zero in case of the basic model.

Day-ahead auction

Cost of day-ahead auction over all trading intervals is calculated as $\sum_{z=1}^{Z} p_{ln,z} \lambda_{ln,z}$, where $p_{ln,z}$ and $\lambda_{ln,z}$ represent unknown power quantity and price (that will be allowed and cleared by ISO) in trading interval *z* at local node (*ln*). Total revenue from end-consumers served by LSE, with energy obtained from day-ahead auction, is calculated as $\sum_{z=1}^{Z} p_{ln,z} \gamma_{ln}$ where γ_{ln} is flat-rate agreed with the end-consumers at local node (*ln*). Substituting the expressions for revenue and cost of day-ahead auction in equation (5.1) gives the following return of day-ahead auction, r_{daa},

$$r_{daa} = \frac{\sum_{z=1}^{Z} p_{ln,z} \gamma_{ln}}{\sum_{z=1}^{Z} p_{ln,z} \lambda_{ln,z}} - 1 \tag{6.56}$$

Equation (6.56) is a general expression for return of day-ahead auction over a total of *Z* trading intervals. Although LSE *l* does not know $p_{ln,z}$, the power quantity that will be allowed by ISO in trading interval *z*, it is interested in exploring the possibility of allocating maximum feasible power quantity allocation to the day-ahead auction,

$p^{DAA}_{ln,\max}$, in all trading intervals. Therefore, return for the day-ahead auction, r_{daa}, is obtained by substituting $p_{ln,z}$ with $p^{DAA}_{ln,\max}$ in (6.56),

$$r_{daa} = \frac{\sum_{z=1}^{Z} p^{DAA}_{ln,\max}\gamma_{ln}}{\sum_{z=1}^{Z} p^{DAA}_{ln,\max}\lambda_{ln,z}} - 1 \tag{6.57}$$

Equation (6.57) is applicable to both basic and improved models of portfolio optimization over a total of *Z* trading intervals. Again, γ_{ln} is assumed certain in(6.57), at the time of portfolio optimization, however, value of $\lambda_{ln,z}$ is uncertain because $\lambda_{ln,z}$ represents LMP at local node in interval *z*. Due to same reasons as already explained for non-local bilateral transaction, and the uncertainty of $\lambda_{ln,z}$, λ_{ln} is defined as a random variable that represents LMP at local node, irrespective of trading interval. Substituting λ_{ln} for $\lambda_{ln,z}$ in (6.57) yields,

$$r_{daa} = \frac{\sum_{z=1}^{Z} p^{DAA}_{ln,\max}\gamma_{ln}}{p^{DAA}_{ln,\max} \times Z \times \lambda_{ln}} - 1 \tag{6.58}$$

Due to the uncertainty of λ_{ln}, expected return for the day-ahead auction is not the same as return of day-ahead auction represented by (6.58). Expected return, $E(r_{daa})$, depends on expectation of LMP at local node, $E(\lambda_{ln})$. Substituting $E(\lambda_{ln})$ for λ_{ln} and $E(r_{daa})$ for r_{daa} in (6.58) leads to,

$$E_{daa} = E(r_{daa}) = \frac{\sum_{z=1}^{Z} p^{DAA}_{ln,\max}\gamma_{ln}}{p^{DAA}_{ln,\max} \times Z \times E(\lambda_{ln})} - 1 \tag{6.59}$$

Equation (6.59) shows that an LSE’s expected return for day-ahead auction, $E(r_{daa})$, is inversely proportional to overall expectation of LMP at local node, $E(\lambda_{ln})$, during the decision period.

An LSE needs to evaluate its expected return for each trading option, as explained above. The expected returns count towards the "return" aspect in the risk-return trade-off evaluated by portfolio optimization, as discussed in introduction of this Chapter.

6.4.3.2 Variances of Returns from Trading Options

In addition to evaluating the "return" aspect in the risk-return trade-off, GenCo needs to evaluate the "risk" aspect. The risk evaluation involves calculation of variance in return of each trading option as well as covariance between returns of all trading options. Equations for variance in return of each trading option are developed as follows.

Local Financial Bilateral Transactions

Since return of local bilateral transaction of an LSE is constant and variance of a constant is zero, variance of return for local bilateral transaction is zero,

$$\sigma^2(r_{lb}) = 0 \tag{6.60}$$

Non-local Financial Bilateral Transactions

In order to develop equation for variance of return for non-local bilateral transaction, equation (6.54) is rearranged, to separate terms containing random variables and terms consisting of constants, as follows,

$$r_i = \frac{\sum_{z=1}^{Z} p_{i,\max}^{FBT} \gamma_{ln}}{\sum_{z=1}^{Z} p_{i,\max}^{FBT} \pi_i} - \left\{ \frac{\left(p_{i,\max}^{FBT} - FTR_i^{held,quantity}\right) \times Z}{\sum_{z=1}^{Z} p_{i,\max}^{FBT} \pi_i} \right\} \left(\lambda_{ln} - \lambda_i\right) - 1 \tag{6.61}$$

As equation (6.61) shows, random variables of LMPs at local node and GenCo node i, λ_{ln} and λ_i, introduce uncertainty in return of non-local bilateral transaction. Consequently, non-local bilateral transaction is a risky trading option that requires a risk assessment. Variance is a measure of risk that can be used for the risk analysis.

Equation (6.61) is a function of two random variables and variance has following property for such functions of two random variables,

$$Var\left(a+b\left(X-Y\right)+c\right)=b^{2}\left(Var\left(X\right)+Var\left(Y\right)-2Cov\left(X,Y\right)\right) \qquad (6.62)$$

where a, b and c are constants and X and Y are random variables. Applying the property of variance (6.62) to equation (6.61) results in following expression for variance of return for non-local bilateral transaction with GenCo at node i, $\sigma^{2}(r_i)$,

$$\sigma_i^2=\sigma^2(r_i)=\left\{\frac{Z\left(p_{i,\max}^{FBT}-FTR_i^{held,quantity}\right)}{\sum_{z=1}^{Z}p_{i,\max}^{FBT}\pi_i}\right\}^2\begin{pmatrix}\sigma^2(\lambda_{ln})+\sigma^2(\lambda_i)\\ -2\sigma(\lambda_{ln},\lambda_i)\end{pmatrix} \qquad (6.63)$$

$$i=1,\cdots,N, i\neq ln$$

Expression (6.63) is valid for both basic and improved models of portfolio optimization but $FTR_i^{held,quantity}$ is set to zero in case of the basic model.

Day-ahead Auction

In order to develop equation for variance of return for day-ahead auction, terms in both numerator and denominator of equation (6.58) are cancelled with each other and the equation is rearranged, to show that random variable is in denominator,

$$r_{daa}=\frac{\gamma_{ln}}{\lambda_{ln}}-1 \qquad (6.64)$$

In equation (6.64), random variable of LMP at local node, λ_{ln}, introduces uncertainty in the return of day-ahead auction. Since day-ahead auction is a risky trading option that requires a risk assessment, variance can be used for the risk analysis. Equation (6.64) is a function of a random variable in denominator and variance has following property for such functions,

$$Var\left(\frac{a}{X}\right) = \frac{a^2}{\left(E(X)\right)^4} Var(X) \tag{6.65}$$

where a is a constant, X is a random variable and $E(X)$ is expectation of X. Applying property of variance (6.65) to equation (6.64) results in following expression for variance of return for day-ahead auction, $\sigma^2(r_{daa})$,

$$\sigma_{daa}^2 = \sigma^2(r_{daa}) = \frac{\left(\gamma_{ln}\right)^2}{\left(E(\lambda_{ln})\right)^4} \sigma^2(\lambda_{ln}) \tag{6.66}$$

where $E(\lambda_{ln})$ is expectation of λ_{ln}, calculated by formula given in Chapter 5.

6.4.3.3 Covariance between Returns from Trading Options

In addition to variance of each return, covariance between returns of all trading options can also contribute to risk. Therefore risk evaluation must explore covariance between returns of all trading options, as discussed next.

Covariance between Returns of Risk-free Local Financial Bilateral Transaction and Risky Non-local Financial Bilateral Transaction

Since return of local bilateral transaction of an LSE is a constant and covariance between a constant and another constant/variable is zero, covariance between return of a local bilateral (*lb*) and return of any non-local bilateral transaction is zero,

$$\begin{gathered} \sigma(r_{lb}, r_i) = 0 \\ i = 1, \cdots, N, i \neq ln \end{gathered} \tag{6.67}$$

Covariance between Returns of Risk-free Local Financial Bilateral Transaction and Risky Day-ahead Auction

Since return of local bilateral transaction of an LSE is a constant and covariance between a constant and another constant/variable is zero, covariance between return of local bilateral transaction and return of day-ahead auction is zero,

$$\sigma(r_{lb}, r_{daa}) = 0 \tag{6.68}$$

Covariance between Returns of a Risky Non-local Financial Bilateral Transaction and another Risky Non-local Financial Bilateral Transaction

In order to develop an equation for covariance among returns of non-local bilateral transactions, equation (6.61) for return of non-local bilateral transaction with GenCo at node *i* needs to be rearranged as,

$$r_i = \left\{ \frac{\sum_{z=1}^{Z} p_{i,\max}^{FBT} \gamma_{ln}}{\sum_{z=1}^{Z} p_{i,\max}^{FBT} \pi_i} - 1 \right\} - \left\{ \frac{\left(p_{i,\max}^{FBT} - FTR_i^{held,quantity} \right) \times Z}{\sum_{z=1}^{Z} p_{i,\max}^{FBT} \pi_i} \right\} \left(\lambda_{ln} - \lambda_i \right) \tag{6.69}$$

Similarly, equation for return of non-local bilateral transaction with GenCo at node *j* can be represented by,

$$r_j = \left\{ \frac{\sum_{z=1}^{Z} p_{j,\max}^{FBT} \gamma_{ln}}{\sum_{z=1}^{Z} p_{j,\max}^{FBT} \pi_i} - 1 \right\} - \left\{ \frac{\left(p_{j,\max}^{FBT} - FTR_j^{held,quantity} \right) \times Z}{\sum_{z=1}^{Z} p_{j,\max}^{FBT} \pi_j} \right\} \left(\lambda_{ln} - \lambda_j \right) \tag{6.70}$$

As equations (6.69) and (6.70) show, random variables of LMPs at local node as well as GenCo nodes *i* and *j* (i.e. λ_{ln}, λ_i and λ_j) introduce uncertainty in returns of the non-local bilateral transactions. Consequently, both non-local bilateral transactions are risky trading options and relationship between the two risks can be evaluated by covariance. Both (6.69) and (6.70) are functions of two random variables and covariance has following property for such functions of two random variables,

$$Cov\left(a - b\left(X - Y\right), c - d\left(X - Z\right)\right) = bd \begin{pmatrix} Var\left(X\right) - Cov\left(X, Z\right) \\ -Cov\left(Y, X\right) + Cov\left(Y, Z\right) \end{pmatrix} \tag{6.71}$$

where *a*, *b*, *c* and *d* are constants and *X*, *Y* and *Z* are random variables. Applying the property of covariance (6.71) to (6.69) and (6.70) results in following expression for covariance between returns of non-local bilateral transactions with GenCos at nodes *i* and *j*, $\sigma(r_i, r_j)$,

$$\sigma_{i,j} = \sigma(r_i, r_j) = \left\{ \begin{array}{l} \left\{ \left(\dfrac{Z\left(p_{i,\max}^{FBT} - FTR_i^{held,quantity}\right)}{\sum\limits_{z=1}^{Z} p_{i,\max}^{FBT} \pi_i} \right) \times \\ \left(\dfrac{Z\left(p_{j,\max}^{FBT} - FTR_j^{held,quantity}\right)}{\sum\limits_{z=1}^{Z} p_{j,\max}^{FBT} \pi_j} \right) \right\} \end{array} \right\} \begin{Bmatrix} \sigma^2(\lambda_{ln}) \\ -\sigma(\lambda_{ln}, \lambda_i) \\ -\sigma(\lambda_{ln}, \lambda_j) \\ +\sigma(\lambda_i, \lambda_j) \end{Bmatrix} \tag{6.72}$$

$$i = 1, \cdots, N, i \neq ln, \; j = 1, \cdots, N, \; j \neq ln, \; j \neq i$$

Expression (6.72) is valid for both basic and improved models of portfolio optimization but $FTR_i^{held,quantity}$ and $FTR_i^{held,quantity}$ are set to zero in case of the basic model.

Covariance between Returns of a Risky Non-local Financial Bilateral Transaction and Risky Day-ahead Auction

Since non-local bilateral transactions and day-ahead auction are both risky, covariance between return of a non-local bilateral transaction and return of day-ahead auction need to be determined. Although covariance property (6.71) is known for finding covariance between two linear functions of random variables, no covariance property was found for a function with a random variable in denominator, such as (6.64). Therefore, in order to determine covariance between return of a non-local bilateral transaction and return of day-ahead auction by (6.71) , equation (6.64) need to be written in the form of a linear function. Moreover, first two terms of the Taylor Series can provide a linear function approximation of equation (6.64). The Taylor Series is a power series expansion of an infinitely differentiable function around some specified point. For instance, Taylor Series for a function $f(X)$ of random variable *X* around specified point $X = \mu$, is given as,

$$f(X) \approx f(\mu) + \frac{f'(\mu)(X-\mu)}{1!} + \frac{f''(\mu)(X-\mu)^2}{2!} + \cdots \tag{6.73}$$

where $f'(\mu)$ is first derivative of f evaluated at μ, $f''(\mu)$ is second derivative of f evaluated at μ, and so on.

Using Taylor Series expansion (6.73) for (6.64), up to the first two terms and around expectation of λ_{ln}, $E(\lambda_{ln})$, yields,

$$r_{daa} \approx \left(\frac{\gamma_{ln}}{E(\lambda_{ln})} - 1\right) + \left(-\frac{\gamma_{ln}}{\left(E(\lambda_{ln})\right)^2}\left(\lambda_{ln} - E(\lambda_{ln})\right)\right) \tag{6.74}$$

Rearranging (6.74) to separate terms containing random variable λ_{ln} and terms consisting of constants gives,

$$r_{daa} \approx \left(\frac{2\gamma_{ln}}{E(\lambda_{ln})} - 1\right) - \left(\frac{\gamma_{ln}}{\left(E(\lambda_{ln})\right)^2}\right)\lambda_{ln} \tag{6.75}$$

For ready reference, equation for return of non-local bilateral transaction with GenCo at node *i* is reproduced below,

$$r_i = \left\{\frac{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\gamma_{ln}}{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\pi_i} - 1\right\} - \left\{\frac{\left(p_{i,\max}^{FBT} - FTR_i^{held,quantity}\right)\times Z}{\sum_{z=1}^{Z} p_{i,\max}^{FBT}\pi_i}\right\}\left(\lambda_{ln} - \lambda_i\right) \tag{6.76}$$

As shown in equations (6.75) and (6.76), random variables of LMPs at local node and GenCo node *i* (i.e. λ_{ln} and λ_i) introduce uncertainty in the returns. Consequently, both trading options are risky and relationship between the two risks can be evaluated by covariance. Both (6.75) and (6.76) are functions of random variables and covariance has following property for such functions of random variables,

$$Cov\left(a - b(X), c - d(X - Y)\right) = bd\left(Var(X) - Cov(X, \mathrm{Y})\right) \tag{6.77}$$

where *a*, *b*, *c* and *d* are constants and *X* and *Y* are random variables. Applying the property of covariance (6.77) to (6.75) and (6.76) yields following expression for covariance between returns of day-ahead auction non-local bilateral transaction with GenCo at nodes *i*, $\sigma(r_{daa}, r_j)$,

$$\sigma_{daa,i} = \sigma(r_{daa}, r_i) = \left\{ \begin{array}{l} \left(\dfrac{Z\left(p_{i,\max}^{FBT} - FTR_i^{held,quantity}\right)}{\sum\limits_{z=1}^{Z} p_{i,\max}^{FBT} \pi_i} \right) \times \\ \left\{ \dfrac{\gamma_{ln}}{\left(E(\lambda_{ln})\right)^2} \right\} \times \left\{ \begin{array}{l} \sigma^2(\lambda_{ln}) \\ -\sigma(\lambda_{ln}, \lambda_i) \end{array} \right\} \end{array} \right\} \quad (6.78)$$

$$i = 1, \cdots, N, i \neq ln$$

Expression (6.78) is valid for both basic and improved models of portfolio optimization but $FTR_i^{held,quantity}$ is set to zero in case of the basic model.

6.4.4 Objective or Utility Function of Portfolio Optimization

For LSE *l*, overall expected return, $E(r_l)$, is sum of its expected returns from *N*+1 trading options, expressed as,

$$E(r_l) = \sum_{\tau=1}^{N+1} x_\tau E_\tau \quad (6.79)$$

where τ is a trading option out of total *N*+1 trading options, x_τ is decision variable for power allocation fraction of *Base Load* to trading option τ and E_τ is expected return for trading option τ.

An LSE's overall variance of return, $\sigma^2(r_l)$, is expressed by sum of its variances and covariance of returns from *N*+1 trading options, as follows,

$$\sigma^2(r_l) = \sum_{\tau=1}^{N+1} x_\tau^2 \sigma_\tau^2 + \sum_{\tau=1}^{N+1} \sum_{\substack{\tau'=1 \\ \tau' \neq \tau}}^{N+1} x_\tau x_{\tau'} \sigma_{\tau,\tau'} \quad (6.80)$$

where τ is a trading option out of total N+1 trading options, τ' is another trading option (different from τ, i.e. $\tau' \neq \tau$) out of total N+1 trading options, power allocation fractions of *Base Load* for trading option τ and τ' are denoted by decision variables x_τ and $x_{\tau'}$ respectively, σ_τ^2 is variance of return for trading option τ and $\sigma_{\tau,\tau'}$ is covariance between returns of trading options τ and τ'.

Substituting expression of overall expectation from (6.79) and variance from (6.80) into overall utility function (5.32) leads to,

$$U_l = \sum_{\tau=1}^{N+1} x_\tau E_\tau - \frac{1}{2} A \left\{ \sum_{\tau=1}^{N+1} x_\tau^2 \sigma_\tau^2 + \sum_{\tau=1}^{N+1} \sum_{\substack{\tau'=1 \\ \tau' \neq \tau}}^{N+1} x_\tau x_{\tau'} \sigma_{\tau,\tau'} \right\} \tag{6.81}$$

where U_l is LSE l's overall utility of portfolio optimization and A is risk aversion factor that shows how strongly the LSE wants to avoid risk.

6.4.5 Optimal Portfolio of Trading Options

An LSE can obtain its optimal portfolio, i.e. optimal power allocation fractions of *Base Load* to trading options, by maximizing the utility function (6.81) as follows,

$$\text{Maximize}_{x_\tau, x_{\tau'}} \; U_l = \sum_{\tau=1}^{N+1} x_\tau E_\tau - \frac{1}{2} A \left\{ \sum_{\tau=1}^{N+1} x_\tau^2 \sigma_\tau^2 + \sum_{\tau=1}^{N+1} \sum_{\substack{\tau'=1 \\ \tau' \neq \tau}}^{N+1} x_\tau x_{\tau'} \sigma_{\tau,\tau'} \right\} \tag{6.82}$$

subject to

$$\begin{gathered} \sum_{\tau=1}^{N+1} x_\tau = 1 \\ 0 \leq x_\tau \leq x_{\tau,max} \end{gathered} \tag{6.83}$$

where x_τ represents power allocation fraction of *Base Load* to trading option τ, out of total N+1 trading options, and $x_{\tau,max}$ denotes upper limit on power allocation fraction to trading option τ.

The optimization problem (6.82)-(6.83) can be solved by any standard non-linear programming solver. Matlab function for constrained non-linear programming, *fmincon,* is used to solve the optimization problem in this thesis.

6.4.6 Optimal Power Quantity Allocations to Trading Options

Optimal power allocation fractions of an LSE's *Base Load* are used to calculate optimal power quantities allocated to trading options. The calculation methods for risky day-ahead auction as well as risk-free local and non-local Financial Bilateral Transactions are described next.

6.4.6.1 Risky day-ahead auction

Optimal power allocation fraction to the day-ahead auction, $x_{ln,opt}^{DAA}$, determines optimal power quantity allocation to risky day-ahead auction, $p_{ln,opt}^{DAA}$, as,

$$p_{ln,opt}^{DAA} = x_{ln,opt}^{DAA} \times p_l^{base} \qquad (6.84)$$

6.4.6.2 Risk-free non-local Financial Bilateral Transactions:

Optimal power quantity allocation to the risky non-local Financial Bilateral Transaction, $p_{i,opt}^{FBT}$, depends on optimal power allocation fraction to bilateral transaction with LSE at node *i*, $x_{i,opt}^{FBT}$,

$$p_{i,opt}^{FBT} = x_{i,opt}^{FBT} \times p_l^{base} \qquad (6.85)$$

6.4.6.3 A risk-free local Financial Bilateral Transaction:

Optimal power allocation fraction to risk-free local bilateral (*lb*) transaction, $x_{lb,opt}^{FBT}$, determines optimal power quantity allocation to the local bilateral (*lb*) transaction, $p_{lb,opt}^{FBT}$, as,

$$p_{lb,opt}^{FBT} = x_{lb,opt}^{FBT} \times p_l^{base} \qquad (6.86)$$

6.5 Portfolio Optimization Procedure of a Load Serving Entity

Each LSE needs to do statistical analysis of LMPs (by formulae presented in Chapter 5) in the previous year before portfolio optimization for the next year. An LSE is responsible for transmission congestion charges so it buys power from GenCos at their local nodes. As a result, an LSE sets overall expectation of LMP at local node $E(\lambda_{ln})$ as assumed price for local bilateral transaction and overall expectation of LMP at GenCo nodes $E(\lambda_i)$ as assumed prices for non-local bilateral transactions. Portfolio optimization procedure of a Load Serving Entity consists of following steps.

1. If using **Basic Portfolio Optimization Procedure** then compute maximum feasible power quantity allocations to trading options by equations (6.35), (6.36) and(6.38).
2. If using **Improved Portfolio Optimization Procedure** then compute maximum feasible power quantity allocations to trading options by equations(6.35), (6.37) and (6.39).
3. Compute upper limits of decision variables for power allocations to trading options by equations (6.40), (6.41) and (6.42).
4. Compute expected return for all trading options by equations (6.45), (6.55) and (6.59).
5. Compute variance of return for all trading options by equations (6.60), (6.63) and (6.66).
6. Compute covariance of return for all trading options by equations (6.67), (6.68), (6.72) and (6.78).
7. Solve portfolio optimization problem defined by (6.82)-(6.83).
8. Compute optimal power quantity allocations to trading options by equations (6.84), (6.85) and (6.86).

6.6 Case Studies

Case studies of this chapter are used to explore advantages of the improved portfolio optimization procedures over the basic portfolio optimization procedures of GenCo and LSE. Results of the basic and improved portfolio optimization procedures of GenCo/LSE are compared with each other to demonstrate benefits of the improvement.

Complete data of test grid used for simulation in FABS, provided in Appendix A, shows that five GenCos and three LSEs are connected to the five node test grid. Although the developed portfolio optimization models are generic, this thesis has only tested the portfolio optimization procedures on the five node test grid. Performance of the portfolio optimization procedures needs to be verified for larger test grids as future work. Each GenCo's and LSE's input data for its portfolio optimization is sent from Java environment of FABS to Matlab and the output data is retrieved back to FABS. The input data of every GenCo and LSE includes expectation, variance and covariance of return for its each trading option. Risk aversion factor and upper limits of decision variables are also part of the input data. A GenCo's (LSE's) portfolio optimization determines optimal power allocation fractions of *Capacity* (*Base Load*) to all trading options.

6.7 Results

Since all GenCos have similar portfolio optimization results, only results of GenCo-3 are discussed here. GenCo-3 is chosen for the discussion because its results, shown in Figure 6.1, most clearly demonstrate all salient features of the improved portfolio optimization procedure. Since GenCo-3 has a total capacity of 520MW and generator outage is not included in our model, it is assumed that GenCo-3 makes power allocation decisions for a maximum of 520MW. The Figure 6.1 shows that, the basic portfolio optimization procedure allocates 173MW for trade with each LSE. The allocations to LSEs add up to the GenCo's total 520MW generation capacity. Due to risk of uncertain market prices, basic portfolio optimization procedure does not allocate any power to the day-ahead auction. The next paragraph explains reasons for equally dividing the total 520MW among LSEs by allocating 173MW for sale to each LSE.

Since GenCo is not responsible for transmission congestion charges its bilateral transactions are risk-free and have zero variance and covariances. Moreover, as shown in equations (6.12) and (6.15), formulae for expected returns of all bilateral transactions have similar composition. Therefore, the basic portfolio optimization procedure determines that each bilateral transaction has an equally good expected return. Consequently, it equally divides the total 520MW among LSEs by allocating 173MW for sale to each LSE.

Figure 6.1 also includes results of GenCo's improved portfolio optimization procedure. The improved model considers maximum quantities of simultaneously feasible non-local Financial Bilateral Transactions announced by ISO for a GenCo. For that reason, instead of allocating 173MW to LSE-1 like the basic procedure, the improved procedure limits the allocation to 93MW that ISO has announced to be feasible. Furthermore, the improved model considers maximum load requirement reported by the local LSE-2 and allocates 234MW instead of 173MW allocated by the basic procedure.

For reasons explained in Chapter 5, ISO does not allow a bilateral transaction if expectation of LMP at LSE node is lower than expectation of LMP at GenCo node. Expectation of LMP at local node of LSE-3 is \$78.9/MWh, whereas the expectation of LMP at local node of GenCo-3 is \$165.0/MWh. Therefore, the improved procedure does not allocate any power for trade with LSE-3. Figure 6.2 shows that the improved procedure avoids over allocation to LSE-1 and under allocation to LSE-2. Consequently, the improved procedure of GenCo avoids loss of bilateral transaction opportunities by choosing power allocations that are feasible and within limits allowed by the ISO or reported by the local LSE.

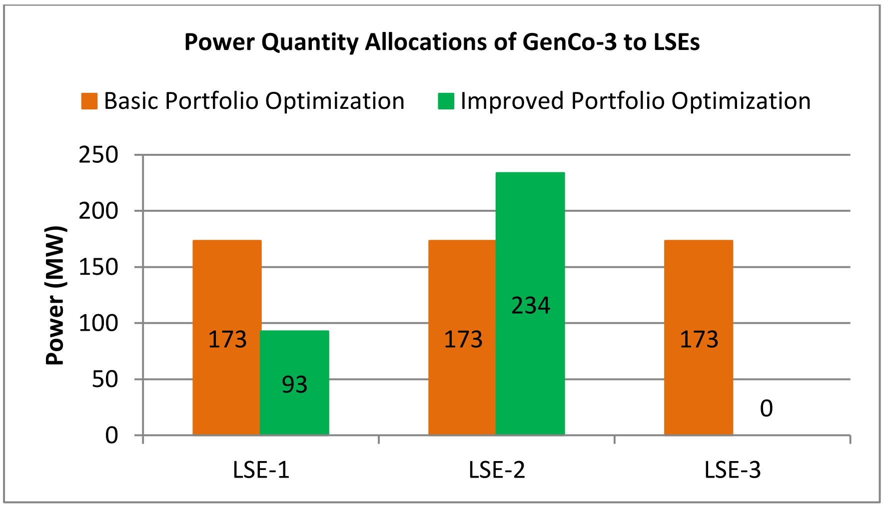

Figure 6.1 Comparison of Power Quantity Allocations of GenCo-3 to LSEs by the Basic and Improved Portfolio Optimization Procedures

Since all LSEs have similar portfolio optimization results, only results of LSE-3 are discussed here. LSE-3 is chosen for the discussion because its results, shown in Figure 6.2, most clearly demonstrate all salient features of the improved portfolio optimization procedure. Since LSE-3 has a base load of 195MW, it is assumed that LSE-3 is interested in bilateral trade of up to 195MW. Figure 6.2 shows that, the basic portfolio optimization procedure allocates bulk of its base load, 182MW out of the 195MW, for purchase from GenCo-4 because this purchase at local node is free of transmission congestion risk. Out of the remaining 13MW, the basic portfolio optimization procedure allocates 3MW, 2MW and 8MW to GenCo-1, GenCo-2 and GenCo-5 respectively. Due to transmission congestion risks, the basic procedure's power allocations to non-local bilateral trades are negligible as compared to risk-free local bilateral trade.

Figure 6.2 also shows results of LSE's improved portfolio optimization procedure. The improved model considers available FTRs and maximum quantities of simultaneously feasible non-local Financial Bilateral Transactions announced by ISO. Since FTRs hedge uncertain transmission congestion costs for non-local bilateral trades, the improved procedure allocates the maximum feasible 16MW, 15MW and 89MW to GenCo-1, GenCo-2 and GenCo-5 respectively, compared to the negligible allocations by the basic procedure. Therefore, instead of relying on a single local bilateral trade suggested by the basic procedure, the improved procedure recommends local as well as non-local bilateral trades. Due to the reasons mentioned in discussion of results for GenCo-3, the LSE's improved procedure does not allocate any power to bilateral trade with GenCo-3.

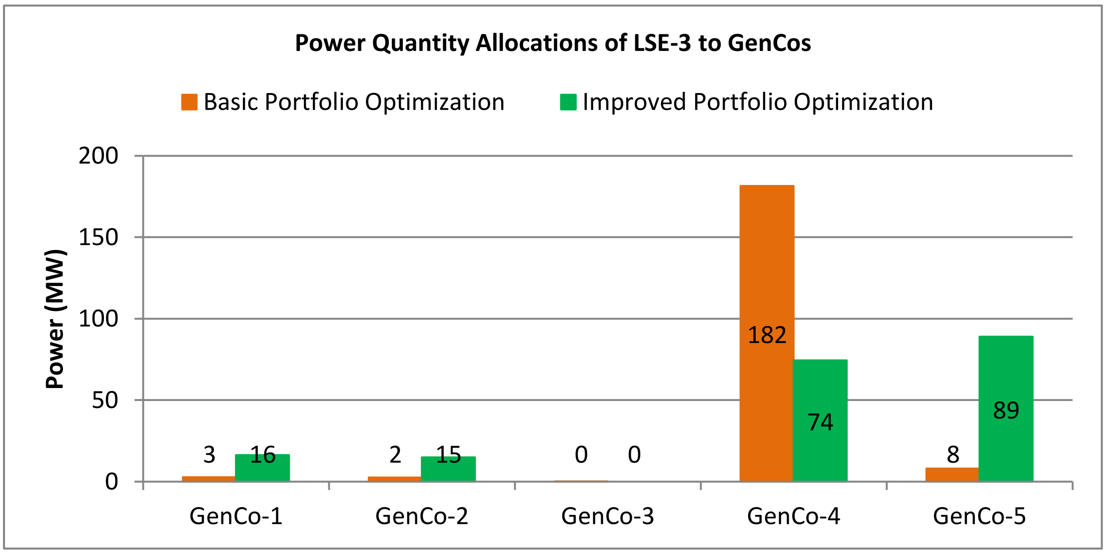

Figure 6.2 Comparison of Power Quantity Allocations of LSE-3 to GenCos by the Basic and Improved Portfolio Optimization Procedures

6.8 Conclusions

Portfolio optimization model in [1], that does not consider maximum levels of simultaneously feasible Financial Bilateral Transactions, is used as the basic portfolio optimization model of a GenCo in FABS. Moreover, a basic portfolio optimization model of an LSE is obtained for FABS on the pattern of the basic portfolio optimization model of GenCo in [1]. Maximum levels of simultaneously feasible Financial Bilateral Transactions are included in the basic portfolio optimization models to develop improved portfolio optimization models for a GenCo and an LSE. Since LSE is responsible for transmission congestion charges, its improved portfolio optimization model also incorporates Financial Transmission Rights. Both basic and improved mathematical models of portfolio optimization for GenCo and LSE are included in FABS.

Risk-averse market participants prefer more bilateral transactions because these reduce risks associated with sudden and severe price fluctuations in day-ahead market. Use of basic portfolio optimization procedures by market participants and subsequent reduction of bilateral transactions by ISO can result in loss of opportunity for market participants. Research work presented in this Chapter has improved basic portfolio optimization procedures by incorporating Financial Transmission Rights held by market participants and taking care of maximum limits on bilateral transactions. Compared to the basic portfolio optimization procedures, improved portfolio optimization procedures of GenCos and LSEs recommend diversified portfolios of bilateral trades that are allowed by ISO because of simultaneous feasibility. Moreover, every GenCo and LSE can run its portfolio optimization procedure for a range of prices and use the results for match making and bilateral negotiations, as shown in the next two Chapters.

6.9 References

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7 Matchmaking Algorithms for Generators and Loads

7.1 Introduction

Portfolio optimization procedures, presented in Chapter 6, were used to determine quantities of power allocations for Financial Bilateral Transactions. The portfolio optimization procedures assumed that bilateral transactions take place at prices equal to overall expectations of LMPs at GenCos' nodes. Thus the portfolio optimization procedures assumed that bilateral transactions are agreed by match making for power quantities at fixed energy prices, i.e. without bilateral negotiations for power quantities or prices. Match makings and bilateral negotiations, explained in the following paragraphs, are two phases of practical market participants' decision making for bilateral transactions.

Match making can be organized through a bulletin-board/broker or can be achieved by direct-search for suitable bilateral transaction partners. Short-duration bilateral transactions, for less than six months, usually result from organized match making. However, direct-search match making is normally used for medium-duration bilateral transactions, typically lasting a year or more. This thesis is concerned with modelling the medium-duration direct-search bilateral transactions because market participants use them as primary hedge against uncertain outcomes of participating in day-ahead markets whereas the short-duration organized bilateral transactions serve as a secondary hedge. Day-ahead auction involves risks such as sudden price spikes and entering into appropriate bilateral transactions can hedge such risks.

When match making is *organized* through a bulletin-board then there is no need for bilateral negotiations. However, if a broker organizes a match making between market participants then they usually need bilateral negotiations to reach agreements. In case of *direct-search* match making, each market participant individually evaluates its bilateral transaction options and determines optimal, risk-minimizing and return-maximizing, energy prices and quantities for the trading options. Consequently, multi-round bilateral negotiations between matched market participants can potentially lead to agreements on power quantities and prices for bilateral transactions.

Since FABS, "Financial transmission instruments, energy Auction and Bilateral transaction Simulator for wholesale electricity markets", models medium-duration *direct-search* bilateral transactions, it also incorporates a bilateral negotiations model. In order to prepare for bilateral negotiations, each GenCo and LSE achieves its *direct-search* match making by conducting portfolio optimization over a range of negotiable prices, instead of a fixed price as shown in Chapter 6. This *direct-search* match making method enables each participant to systematically explore available trading options for bilateral transactions, over the entire range of negotiable prices and throughout the market.

Even in a decentralized market scenario, it can be expected that some kind of a bilateral transaction protocol becomes an industry wide standard. Such a uniform protocol will avoid haphazard behaviour by participants and keep bilateral transaction process in order. In FABS, it is assumed that a bilateral transaction protocol has already been agreed between all participants prior to match making.

Each market participant needs to know its negotiable price sets to undertake its private match making because match making results prepare it for bilateral negotiations in which it can only propose prices within the *negotiable price sets*. A market participant's collection of *negotiable price sets* contains a *negotiable price set* for each of its bilateral transaction options. The three rules of the bilateral transaction protocol that govern validity of *negotiable price sets* are listed as follows and discussed in the next three paragraphs.

1. Expectation of LMP at a GenCo node acts as *reference price* for bilateral negotiation between the GenCo and LSEs.
2. Participants can propose prices that only deviate up to a certain extent, termed *price deviation*, from the *reference price*.

3. A valid *negotiable price set* is a set of discrete prices at *price intervals* of \$0.1/MWh.

It is important to remember that energy prices in day-ahead markets serve as reference prices for Financial Bilateral Transactions in electricity markets of USA [1]. In FABS, a GenCo is not responsible for transmission congestion charges because it sells energy to LSEs at its local node. An LSE is liable to pay transmission congestion charges for transfer of energy bought form GenCos at their local nodes to its own node. Since sale and purchase of energy takes place at a GenCo node, the bilateral transaction protocol fixes the expectation of LMP at the GenCo node as a *reference price* for bilateral trading between the GenCo and all LSEs. The *reference price* of a bilateral transaction option becomes the middle price in its *negotiable price set.*

In addition to specifying a *reference price* for each bilateral transaction option, the bilateral transaction protocol mandates that, during their multi-round bilateral negotiation, offer prices of a GenCo and bid prices of an LSE can only deviate up to a certain extent, termed *price deviation*, from the *reference price*. Standard deviation of LMP at a node can be used as *price deviation* because it is a measure of the spread of LMP. Simultaneous consideration of all bilateral transaction options by private match making algorithm requires a market participant to explore each trading option, up to the same extent on either side of the option's *reference price*. Furthermore, a market participant needs to use its private match making results for bilateral negotiation with other market participants. Therefore, bilateral transaction protocol requires that all market participants should use the same *price deviation* for all trading options. Since expectations of LMPs at GenCo nodes act as *reference prices*, only standard deviations of LMPs at GenCo nodes are considered for selection as the *price deviation*. Given the set of standard deviations of LMPs at GenCo nodes, the protocol has to specify one of the values as the *price deviation* for all trading options. The protocol chooses the minimum value in the set because LMPs at all GenCo nodes deviate by at least that value. The *reference price* and the *price deviation* of a bilateral transaction option determine the minimum and the maximum prices in its *negotiable price set.*

The protocol also requires that negotiable prices should have a maximum granularity of \$0.1/MWh. It means valid *negotiable price set* for a trading option is a set of discrete prices, specified to one decimal place, at price intervals of \$0.1/MWh. The difference between adjacent prices in each *negotiable price set* is termed *price interval* that remains fixed at \$0.1/MWh. The *reference price,* the *price deviation* and the *price interval* are the three protocol rules that specify each price in a *negotiable price set.* It will be explained in Sections 7.2 and 7.3 that how a GenCo and an LSE uses the three rules to find its *negotiable price sets.*

A detailed literature review of match making simulation techniques for bilateral transactions was presented in Chapter 3. However, a summary of the literature review is provided here. Match making of buyers and sellers is simulated as an *organised* but *random* process in works presented in [2] and [3]. However, *organised* and *systematic* match making is simulated in works presented in [4], [5], [6], [7] and [8]. In case of [4] and [5], match making organiser has *complete information* of energy prices and quantities submitted by all buyers and sellers. Whereas in [6], [7] and [8], match making organiser has *complete information* of private preferences of all buyers and sellers regarding energy prices and quantities. Techniques presented in [2], [3], [4], [5], [6], [7] and [8] are suitable for simulating *match making* of short-duration *organised* bilateral transactions but not medium-duration *direct-search* bilateral transactions.

EMCAS, NEMSIM and MASCEM are commercial software for simulation of electricity markets. Overviews of EMCAS, NEMSIM and MASCEM, presented in [9], [10] and [11] respectively, indicate that bilateral transactions are modelled in these software. Although it is not explicitly stated but these commercial and proprietary software may include models of medium duration *direct-search* bilateral transactions. However, full mathematical models of *match making* are not publicly available to research community for medium duration *direct-search* bilateral transactions. Work presented in this Chapter contributes to knowledge by presenting a mathematical model of *match making* for medium-duration *direct-search* bilateral transactions.

Portfolio optimization methods of GenCos [12] and LSEs [13] do not accommodate limits on bilateral transfer capacities or consider Financial Transmission Rights. However, the portfolio optimization methods were improved, as shown in Chapter 6, to accommodate limits on bilateral transfer capacities and Financial Transmission Rights. This chapter explains details of how the improved portfolio optimization methods are used in match making for *direct-search* bilateral transactions.

Compared to above-mentioned previous works in simulation of match making for bilateral transactions, the match making algorithms in this Chapter have following salient features. Match making for decentralized bilateral transactions is achieved by direct-search without any organized bulletin-board/broker or match making organizer. Portfolio optimization provides a systematic way of considering available options for electricity trading throughout the market instead of some random match making process. Improved portfolio optimization of a market participant considers limits on bilateral transfer capacities and Financial Transmission Rights held by the participant. Each GenCo and LSE can independently determine its own course of action depending on private profit-seeking goals and risk-aversion preferences as well as market history.

The rest of the chapter is organized as follows. Sections 7.2 and 7.3 present details of match making by a Generation Company and a Load Serving Entity respectively. Results and conclusions are presented in Sections 7.4 and 7.5 respectively.

7.2 Match Making by Generation Company

Each GenCo needs to know its *negotiable price sets* to undertake its private match making because match making results prepare it for bilateral negotiations in which GenCo can only make price offers within *negotiable price sets*. A GenCo's collection of *negotiable price sets* contains a *negotiable price set* for each of its bilateral transaction options. Three protocol rules that govern validity of *negotiable price sets* are discussed in the introduction of this Chapter. A GenCo uses the three protocol rules to find its *negotiable price sets* as follows.

Since sale and purchase of energy takes place at a GenCo node, the bilateral transaction protocol fixes the expectation of LMP at the node as a *reference price* for bilateral trading between the GenCo and all LSEs. A GenCo has a set of *reference prices* that contains a *reference price* for each of its bilateral transaction options. Given that expectation of LMP at local node of GenCo *g* is $E\left(\lambda_g\right)$, it sets its *reference price* for bilateral transaction with LSE *l*, $RfPr_l^g$, by,

$$RfPr_l^g = E\left(\lambda_g\right) \tag{7.1}$$

The protocol chooses the minimum value in the set of standard deviations of LMPs at GenCo nodes because LMPs at all GenCo nodes deviate by at least that value. The set is denoted by $D_G = \left\{\sigma\left(\lambda_g\right) : g = 1, 2, \ldots, G\right\}$. According to the protocol, GenCo *g* sets the *price deviation* of its price offers to all LSEs, $PrDv_L^g$, to the minimum value in the set, $Min\left[D_G\right]$, by,

$$PrDv_L^g = Min\left[D_G\right] \tag{7.2}$$

The protocol also requires that each *negotiable price set* of GenCo *g* must be a set of discrete prices at price intervals of \$0.1/MWh. Therefore GenCo sets the *price interval* between discrete prices in all *negotiable price sets*, $\Delta\pi$, as,

$$\Delta\pi = 0.1 \tag{7.3}$$

Reference price (7.1) of a bilateral transaction option becomes the middle price in *negotiable price set* of the option. A GenCo uses a *reference price* (7.1) and the *price deviation* (7.2) of a bilateral transaction option to determine the minimum and the maximum prices in its *negotiable price set.* Given *reference price*(7.1), $RfPr_l^g$, and *price deviation* (7.2), $PrDv_L^g$, GenCo *g* calculates its *minimum negotiable price* for bilateral transaction with LSE *l*, $np_{l,\min}^g$, as,

$$np_{l,\min}^{g} = RfPr_{l}^{g} - PrDv_{L}^{g} \tag{7.4}$$

Similarly, GenCo *g* calculates its *maximum negotiable price* for bilateral transaction with LSE *l*, $np_{l,\max}^{g}$, by,

$$np_{l,\max}^{g} = RfPr_{l}^{g} + PrDv_{L}^{g} \tag{7.5}$$

Knowing the *minimum negotiable price*, $np_{l,\min}^{g}$, the *maximum negotiable price*, $np_{l,\max}^{g}$, and the *price interval*, $\Delta\pi$, GenCo *g*'s valid *negotiable price set* for bilateral transaction with LSE *l*, N_{l}^{g}, is expressed as,

$$N_{l}^{g} = \left\{ np_{l,\min}^{g} + p\Delta\pi : p = 0,1,\ldots,\frac{np_{l,\max}^{g} - np_{l,\min}^{g}}{\Delta\pi} \right\} \tag{7.6}$$

Using equations (7.1)-(7.6), a GenCo finds a valid *negotiable price set* for its each bilateral transaction option.

A GenCo has a natural desire to sell its energy at the highest feasible prices, i.e. at the *maximum negotiable prices* in the *negotiable price sets*. However, it is aware that LSEs would like to buy energy at the lowest feasible prices, i.e. at the *minimum negotiable prices* in the *negotiable price sets*. As a result, a GenCo has to engage in bilateral negotiations over the *negotiable price sets*. It explores the risk-return trade-off of bilateral transaction options over the *negotiable price sets* to prepare for the bilateral negotiations. A GenCo starts the exploration of its bilateral transaction options from the *maximum negotiable prices* and continues the exploration steps, at *price intervals*, $\Delta\pi$, down to the *minimum negotiable prices*. At each step, the *price interval*, $\Delta\pi$, leads to a specific price in each *negotiable price set*. The GenCo evaluates risk-return trade-off of all trading options by conducting portfolio optimization at the specific prices. The portfolio optimization determines optimal power quantity allocation to each trading option.

The sequence of exploration steps functions as a scan over the *negotiable price sets*. In addition to finding the optimal power quantity allocations, the scan involves calculation of each bilateral transaction option's utility. Knowing utility of bilateral transaction option with an LSE, and how it varies over the *negotiable price set*, enables a GenCo to develop its bilateral transaction offers to the LSE for multi-round bilateral negotiations. Method of developing the bilateral transaction offers, consisting of energy price offers and power quantity offers sent by the GenCo to the LSE, will be explained in the next Chapter.

Utility calculation methods for Financial Bilateral Transaction options of a GenCo are explained in Section 7.2.1 and a GenCo's match making algorithm is presented in Section 7.2.2.

7.2.1 Utility Calculation Methods for Bilateral transaction Options of a Generation Company

Using utility function defined by equation (5.32) for a single investment option, a market participant can calculate utility of a generic trading option τ , U_τ , by,

$$U_\tau = E_\tau - \frac{1}{2} A \left(\sigma_\tau^2 + \sum_{\tau'=1, \tau' \neq \tau}^{N+1} \sigma_{\tau,\tau'} \right) \tag{7.7}$$

where A is risk aversion factor, E_τ is expected return from the trading option τ , σ_τ^2 is variance of return from the trading option τ , $\sigma_{\tau,\tau'}$ is covariance between returns of trading options τ and τ', N is the total number of nodes and N+1 are the maximum possible trading options – which include N bilateral transaction options as well as the option of trading by day-ahead auction. Equation (7.7) shows that a trading option's utility depends on expectation, variance and covariances of return for the trading option. Consequently, equation for utility of a trading option can be determined if expectation, variance and covariances of return for the trading option are known.

Before portfolio optimization, a market participant was interested in exploring the possibility of allocating maximum feasible power quantity allocation to a trading option. In consequence, maximum feasible power quantity allocation was used as tentative power quantity in equations, developed in Chapter 6, for expectation, variance and covariances of return for the trading option. However, as a result of the portfolio optimization, a market participant finds optimal power quantity allocation for the trading option. Therefore, for this Chapter, maximum feasible power quantity allocation must be replaced with optimal power quantity allocation in equations, developed in Chapter 6, for expectation, variance and covariances of return for the trading option.

The generic utility equation (7.7) will be used to develop equations for utilities of non-local and local Financial Bilateral Transaction options of a GenCo in Sections 7.2.1.1 and 7.2.1.2 respectively.

7.2.1.1 Risk-free non-local bilateral transaction options

Equation (6.15) was developed in Chapter 6 for a GenCo's expected return from non-local bilateral transaction option with LSE at node *i*, E_i. The equation used maximum feasible power quantity allocation as a tentative quantity. Since optimal power quantity allocation is now known as a result of portfolio optimization, it must replace the tentative quantity in the equation. Replacing tentative quantity, $p_{i,\max}^{FBT}$, by optimal quantity, $p_{i,opt}^{FBT}$, in equation (6.15) yields,

$$E_i = \frac{\sum_{z=1}^{Z} p_{i,opt}^{FBT} \pi_i}{\sum_{z=1}^{Z} \left(a_g \left(p_{i,opt}^{FBT} \right)^2 + b_g p_{i,opt}^{FBT} + c_g \right)} - 1 \tag{7.8}$$

where *z* is a trading interval out of total *Z* trading intervals, a_g, b_g and c_g are actual fuel consumption based coefficients of GenCo and π_i is energy price for the non-local bilateral transaction option.

A GenCo's variance of return from a non-local bilateral transaction option was found to be zero, as shown in equation (6.20). A GenCo's covariances between return from a non-local bilateral transaction option and return from any other trading option were also determined to be zero, as shown in equations (6.23), (6.25) and (6.26). Since variance and covariances of return from a non-local bilateral transaction option are all zero, utility of the trade only depends on expectation from the return. In consequence, substituting the expected return, E_i, from equation (7.8) into generic utility equation (7.7), a GenCo's utility of non-local bilateral transaction option with LSE at node *i*, U_i, can be written as,

$$U_i = \frac{\sum_{z=1}^{Z} p_{i,opt}^{FBT} \pi_i}{\sum_{z=1}^{Z} \left(a_g \left(p_{i,opt}^{FBT} \right)^2 + b_g p_{i,opt}^{FBT} + c_g \right)} - 1 \tag{7.9}$$

7.2.1.2 A risk-free local bilateral transaction option

Equation (6.12) was developed in Chapter 6 for a GenCo's expected return from local bilateral transaction option with LSE at local node, E_{lb}. The equation used maximum feasible power quantity allocation as a tentative quantity. Since optimal power quantity allocation is now known as a result of portfolio optimization, it must replace the tentative quantity in the equation. Replacing tentative quantity, $p_{lb,\max}^{FBT}$, by optimal quantity, $p_{lb,opt}^{FBT}$, in equation (6.12) yields,

$$E_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,opt}^{FBT} \pi_i}{\sum_{z=1}^{Z} \left(a_g \left(p_{lb,opt}^{FBT} \right)^2 + b_g p_{lb,opt}^{FBT} + c_g \right)} - 1 \tag{7.10}$$

where *z* is a trading interval out of total *Z* trading intervals, a_g, b_g and c_g are actual fuel consumption based coefficients of GenCo and π_{lb} is energy price for the local bilateral transaction option.

A GenCo's variance of return from a local bilateral transaction option was found to be zero, as shown in equation (6.20). A GenCo's covariances between return from a local bilateral transaction option and return from any other trading option were also determined to be zero, as shown in equations (6.23) and (6.24). Since variance and covariances of return from a non-local bilateral transaction option are all zero, utility of the trading option only depends on expectation from the return. In consequence, substituting E_{lb} from equation (7.10) into generic utility equation (7.7), a GenCo's utility of local bilateral transaction option with LSE at local node, U_{lb} , can be written as,

$$U_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,opt}^{FBT} \pi_i}{\sum_{z=1}^{Z} \left(a_g \left(p_{lb,opt}^{FBT} \right)^2 + b_g p_{lb,opt}^{FBT} + c_g \right)} - 1 \tag{7.11}$$

7.2.2 Match Making Algorithm of a Generation Company

In FABS, a GenCo uses following match making algorithm that is based on improved portfolio optimization procedure, discussed in Chapter 6, and utility calculation methods, explained in this Chapter. Since the improved portfolio optimization procedure and the utility calculation methods are generic, the match making algorithm of GenCo is also generic. However, this thesis has only tested GenCo's match making algorithm on the five node test grid and the algorithm is yet to be tested on larger grids.

1) Set the *maximum negotiable prices* as assumed prices for bilateral transaction options.
2) **while** assumed prices > *minimum negotiable prices* **do**
    a) Conduct **improved portfolio optimization procedure** of a Generation Company presented in Chapter 6.
    b) Compute individual utility of each non-local bilateral transaction option by equation (7.9).
    c) Compute utility of the local bilateral transaction option by equation (7.11).
    d) Decrease assumed prices for all bilateral transaction options by the *price interval*, $\Delta\pi$, set to \$0.1/MWh by equation (7.3)
3) end while

7.3 Match Making by Load Serving Entity

Each LSE needs to know its *negotiable price sets* to undertake its private match making because match making results prepare it for bilateral negotiations in which LSE can only submit price bids within *negotiable price sets*. An LSE's collection of *negotiable price sets* contains a *negotiable price set* for each of its bilateral transaction options. Three protocol rules that govern validity of *negotiable price sets* are discussed in the introduction of this Chapter. LSE's method of determining the *negotiable price sets*, conforming to the protocol, is described as follows.

Since sale and purchase of energy takes place at a GenCo node, the bilateral transaction protocol fixes the expectation of LMP at the node as a *reference price* for bilateral trading between the GenCo and all LSEs. An LSE has a set of *reference prices* that contains a *reference price* for each of its bilateral transaction options. According to the protocol, LSE *l* sets the expectation of LMP at local node of GenCo *g*, $E\left(\lambda_g\right)$, as its *reference price* for bilateral transaction with the GenCo, $RfPr_g^l$,

$$RfPr_g^l = E\left(\lambda_g\right) \tag{7.12}$$

The protocol chooses the minimum value in the set of standard deviations of LMPs at GenCo nodes because LMPs at all GenCo nodes deviate by at least that value. The set is denoted by $D_G = \left\{\sigma\left(\lambda_g\right): g = 1,2,\ldots,G\right\}$. As specified by the protocol, LSE *l* sets the *price deviation* of its price bids to all GenCos, $PrDv_G^l$, to the minimum value in the set, $Min\left[D_G\right]$, by,

$$PrDv_G^l = Min\left[D_G\right] \tag{7.13}$$

The protocol also requires that each *negotiable price set* of LSE *l* must be a set of discrete prices at price intervals of \$0.1/MWh. Therefore LSE sets the *price interval* between discrete prices in all *negotiable price sets*, $\Delta\pi$, as,

$$\Delta\pi = 0.1 \tag{7.14}$$

Reference price (7.12) of a bilateral transaction option becomes the middle price in *negotiable price set* of the option. An LSE uses a *reference price* (7.12) and the *price deviation* (7.13) of a bilateral transaction option to determine the minimum and the maximum prices in its *negotiable price set.* Using *reference price* (7.12), $RfPr_g^l$, and *price deviation* (7.13), $PrDv_G^l$, LSE l calculates its *minimum negotiable price* for bilateral transaction with GenCo g, $np_{g,\min}^l$, as,

$$np_{g,\min}^l = RfPr_g^l - PrDv_G^l \tag{7.15}$$

Similarly, LSE l calculates its *maximum negotiable price* for bilateral transaction with GenCo g, $np_{g,\max}^l$, by,

$$np_{g,\max}^l = RfPr_g^l + PrDv_G^l \tag{7.16}$$

Using the *minimum negotiable price*, $np_{g,\min}^l$, the *maximum negotiable price*, $np_{g,\max}^l$, and the *price interval*, $\Delta\pi$, LSE l's valid *negotiable price set* for bilateral transaction with GenCo g, N_g^l, is expressed as,

$$N_g^l = \left\{ np_{g,\min}^l + p\Delta\pi : p = 0,1,\ldots,\frac{np_{g,\max}^l - np_{g,\min}^l}{\Delta\pi} \right\} \tag{7.17}$$

Using equations (7.12)-(7.17), an LSE finds a valid *negotiable price set* for its each bilateral transaction option.

An LSE has a natural desire to buy energy at the lowest feasible prices, i.e. at the *minimum negotiable prices* in the *negotiable price sets*. However, it is aware that GenCos would like to sell energy at the highest feasible prices, i.e. at the *maximum negotiable prices* in the *negotiable price sets*. As a result, an LSE has to engage in bilateral negotiations over the *negotiable price sets*. It explores the risk-return trade-off of bilateral transaction options over the *negotiable price sets* to prepare for the bilateral negotiations. An LSE starts the exploration of its bilateral transaction options from the *minimum negotiable prices* and continues the exploration steps, at *price intervals*, $\Delta\pi$, up to the *maximum negotiable prices*. At each step, the *price interval*, $\Delta\pi$, leads to a specific price in each *negotiable price set*. The LSE evaluates risk-return trade-off of all trading options by conducting portfolio optimization at the specific prices. The portfolio optimization determines optimal power quantity allocation to each trading option.

An LSE starts the exploration from the *minimum negotiable prices* in *negotiable price sets* because it would like to buy energy at the lowest feasible prices. The LSE continues its exploration steps, in equal price increments, Δp, from the *minimum negotiable prices* to the *maximum negotiable prices*. In each exploration step, the equal price increment, Δp, leads to a specific price in each *negotiable price set*. The LSE evaluates risk-return trade-off of all trading options by conducting portfolio optimization at the specific prices. The portfolio optimization determines optimal power quantity allocation to each trading option.

The sequence of exploration steps functions as a scan over the *negotiable price sets*. In addition to finding the optimal power quantity allocations, the scan involves calculation of each bilateral transaction option's utility. Knowing utility of bilateral transaction option with a GenCo, and how it varies over the *negotiable price set*, enables an LSE to develop its bilateral transaction bids to the GenCo for multi-round bilateral negotiations. Method of developing the bilateral transaction bids, consisting of energy price bids and power quantity bids sent by the LSE to the GenCo, will be explained in the next Chapter.

Utility calculation methods for Financial Bilateral Transaction options of an LSE are explained in Section 7.3.1 and an LSE's match making algorithm is presented in Section 7.3.2.

7.3.1 Utility Calculation Methods for Bilateral transaction Options of a Load Serving Entity

Using the generic utility equation (7.7), equations for utilities of non-local and local Financial Bilateral Transaction options of an LSE will be developed in Sections 7.3.1.1 and 7.3.1.2 respectively.

7.3.1.1 Risky non-local bilateral transaction options

In Chapter 6, equations were developed for an LSE's expectation, variance and covariances of return from non-local bilateral transaction option with GenCo at node *i*. The equations used maximum feasible power quantity allocation as a tentative quantity. Since optimal power quantity allocation is now known as a result of portfolio optimization, it must replace the tentative quantity in all those equations as discussed next.

Equation (6.55) was developed in Chapter 6 for an LSE's expected return from non-local bilateral transaction option with GenCo at node *i*, E_i . Replacing tentative quantity, $p_{i,\max}^{FBT}$, by optimal quantity, $p_{i,opt}^{FBT}$, in equation (6.55) leads to,

$$E_i = \frac{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\gamma_{ln} - \left\{ Z\left(p_{i,opt}^{FBT} - FTR_i^{held,quantity}\right)\left(E\left(\lambda_{ln}\right) - E\left(\lambda_i\right)\right)\right\}}{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\pi_i} - 1 \qquad (7.18)$$

where z is a trading interval out of total Z trading intervals, γ_{ln} is flat-rate agreed with the end-consumers at local node, π_i is energy price for the non-local bilateral transaction option, $FTR_i^{held,quantity}$ is Financial Transmission Rights (FTR) held by LSE between its local node (*ln*) and GenCo node *i*, $E\left(\lambda_{ln}\right)$ is expectation of LMP at local node and $E\left(\lambda_i\right)$ is expectation of LMP at GenCo node *i*.

In Chapter 6, equation (6.63) represented an LSE's variance of return from non-local bilateral transaction option with GenCo at node *i*, σ_i^2. Replacing tentative quantity, $p_{i,\max}^{FBT}$, by optimal quantity, $p_{i,opt}^{FBT}$, in equation (6.63) yields,

$$\sigma_i^2 = \left\{ \frac{Z\left(p_{i,opt}^{FBT} - FTR_i^{held,quantity}\right)}{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\pi_i} \right\}^2 \begin{pmatrix} \sigma^2(\lambda_{ln}) + \sigma^2(\lambda_i) \\ -2\sigma(\lambda_{ln},\lambda_i) \end{pmatrix} \tag{7.19}$$

where $\sigma^2(\lambda_{ln})$ is variance of LMP at local node, $\sigma^2(\lambda_i)$ is variance of LMP at GenCo node *i* and $\sigma(\lambda_{ln},\lambda_i)$ is covariance between LMPs at local node and node *i*.

Equation (6.72) was developed for an LSE's covariance between return from non-local bilateral transaction option with GenCo at node *i* and return from non-local bilateral transaction option with GenCo at another node *j*, $\sigma_{i,j}$. Replacing tentative quantity, $p_{i,\max}^{FBT}$, by optimal quantity, $p_{i,opt}^{FBT}$, in equation (6.72) gives,

$$\sigma_{i,j} = \left\{ \begin{array}{l} \left(\dfrac{Z\left(p_{i,opt}^{FBT} - FTR_i^{held,quantity}\right)}{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\pi_i} \right) \times \\ \left(\dfrac{Z\left(p_{j,opt}^{FBT} - FTR_j^{held,quantity}\right)}{\sum_{z=1}^{Z} p_{j,opt}^{FBT}\pi_j} \right) \end{array} \right\} \left\{ \begin{array}{l} \sigma^2(\lambda_{ln}) - \sigma(\lambda_{ln},\lambda_i) \\ -\sigma(\lambda_{ln},\lambda_j) + \sigma(\lambda_i,\lambda_j) \end{array} \right\} \tag{7.20}$$

$$j = 1,\cdots,N,\ j \neq ln,\ j \neq i$$

where $\sigma(\lambda_{ln},\lambda_j)$ is covariance of LMP at local node and node *j* and $\sigma(\lambda_i,\lambda_j)$ is covariance between LMPs at nodes *i* and *j*.

In Chapter 6, equation (6.78) represented an LSE's covariance between return from non-local bilateral transaction option with GenCo at node *i* and return from day-ahead auction, $\sigma_{daa,i}$. Replacing tentative quantity, $p_{i,\max}^{FBT}$, by optimal quantity, $p_{i,opt}^{FBT}$, in equation (6.78) leads to,

$$\sigma_{daa,i} = \left\{ \begin{array}{c} \left(\dfrac{Z\left(p_{i,opt}^{FBT} - FTR_i^{held,quantity}\right)}{\sum_{z=1}^{Z} p_{i,opt}^{FBT} \pi_i} \right) \times \\ \left\{ \dfrac{\gamma_{ln}}{\left(E(\lambda_{ln})\right)^2} \right\} \times \left\{ \begin{array}{l} \sigma^2(\lambda_{ln}) \\ -\sigma(\lambda_{ln}, \lambda_i) \end{array} \right\} \end{array} \right\} \tag{7.21}$$

where $E(\lambda_{ln})$ is expectation of λ_{ln}, calculated by formula given in Chapter 5.

An LSE's covariance between return from non-local bilateral transaction option with GenCo at node *i* and return from local bilateral transaction option was found to be zero, as shown in equation (6.67).

Substituting E_i, σ_i^2, $\sigma_{daa,i}$ and $\sigma_{i,j}$, from equations (7.18), (7.19), (7.21) and (7.20) respectively, into generic utility equation (7.7), an LSE's utility of non-local bilateral transaction option with GenCo at node *i*, U_i, can be written as,

$$
\begin{aligned}
&U_i = \\
&\frac{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\gamma_{ln} - \left\{\left(p_{i,opt}^{FBT} - FTR_i^{held,quantity}\right)Z\left(E\left(\lambda_{ln}\right) - E\left(\lambda_i\right)\right)\right\}}{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\pi_i} - 1 \\
&-\frac{1}{2}A\left\{\frac{Z\left(p_{i,opt}^{FBT} - FTR_i^{held,quantity}\right)}{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\pi_i}\right\}^2 \begin{pmatrix}\sigma^2(\lambda_{ln}) + \sigma^2(\lambda_i) \\ -2\sigma(\lambda_{ln},\lambda_i)\end{pmatrix} \\
&-\frac{1}{2}A\left\{\frac{\gamma_{ln}}{\left(E(\lambda_{ln})\right)^2}\right\}\left\{\frac{Z\left(p_{i,opt}^{FBT} - FTR_i^{held,quantity}\right)}{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\pi_i}\right\}\begin{Bmatrix}\sigma^2(\lambda_{ln}) \\ -\sigma(\lambda_{ln},\lambda_i)\end{Bmatrix} \qquad (7.22) \\
&-\frac{1}{2}A\sum_{\substack{j=1,\\ j\neq i,\\ j\neq ln}}^{N}\left\{\begin{array}{l}\left(\dfrac{Z\left(p_{i,opt}^{FBT} - FTR_i^{held,quantity}\right)}{\sum_{z=1}^{Z} p_{i,opt}^{FBT}\pi_i}\right)\times \\ \left(\dfrac{Z\left(p_{j,opt}^{FBT} - FTR_j^{held,quantity}\right)}{\sum_{z=1}^{Z} p_{j,opt}^{FBT}\pi_j}\right)\end{array}\right\}\begin{Bmatrix}\sigma^2(\lambda_{ln}) \\ -\sigma(\lambda_{ln},\lambda_i) \\ -\sigma(\lambda_{ln},\lambda_j) \\ +\sigma(\lambda_i,\lambda_j)\end{Bmatrix}
\end{aligned}
$$

7.3.1.2 A risk-free local bilateral transaction option

Equation (6.45) was developed in Chapter 6 for an LSE's expected return from local bilateral transaction option with GenCo at local node, E_{lb}. The equation used maximum feasible power quantity allocation as a tentative quantity. Since optimal power quantity allocation is now known as a result of portfolio optimization, it must replace the tentative quantity in the equation. Replacing tentative quantity, $p_{lb,\max}^{FBT}$, by optimal quantity, $p_{lb,opt}^{FBT}$, in equation (6.45) yields,

$$
E_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,opt}^{FBT}\gamma_{ln}}{\sum_{z=1}^{Z} p_{lb,opt}^{FBT}\pi_{lb}} - 1 \qquad (7.23)
$$

where z is a trading interval out of total Z trading intervals, γ_{ln} is flat-rate agreed with the end-consumers at local node and π_{lb} is energy price for the local bilateral transaction option.

An LSE's variance of return from a local bilateral transaction option was found to be zero, as shown in equation (6.60). An LSE's covariances between return from a local bilateral transaction option and return from any other trading option were also determined to be zero, as shown in equations (6.67) and (6.68). Since variance and covariances of return from a non-local bilateral transaction option are all zero, utility of the trading option only depends on expectation from the return. In consequence, substituting E_{lb} from equation (7.23) into generic utility equation (7.7), an LSE's utility of local bilateral transaction option with GenCo at local node, U_{lb}, can be written as,

$$U_{lb} = \frac{\sum_{z=1}^{Z} p_{lb,opt}^{FBT} \gamma_{ln}}{\sum_{z=1}^{Z} p_{lb,opt}^{FBT} \pi_{lb}} - 1 \qquad (7.24)$$

7.3.2 Match Making Algorithm of a Load Serving Entity

In FABS, an LSE uses following match making algorithm that is based on improved portfolio optimization procedure, discussed in Chapter 6, and utility calculation methods, explained in this Chapter. Since the improved portfolio optimization procedure and the utility calculation methods are generic, the match making algorithm of LSE is also generic. However, since this thesis has only tested LSE's match making algorithm for the five node test grid, its performance needs to be evaluated for larger test grids as a future work.

1) Set the *minimum negotiable prices* as assumed prices for bilateral transaction options.
2) **while** assumed prices < *maximum negotiable prices* **do**

a) Conduct **improved portfolio optimization procedure** of a Load Serving Entity, presented in Chapter 6.
b) Compute individual utility of each non-local bilateral transaction option by equation (7.22).
c) Compute utility of the local bilateral transaction option by equation (7.24).
d) Increase assumed prices for all bilateral transaction options by the *price interval*, $\Delta\pi$, set to \$0.1/MWh by equation (7.14)

3) end while

7.4 Results

Most power allocation results of GenCos are similar and Figure 7.1 illustrates a typical power allocation result of a GenCo. It shows that for any price in the negotiable price set, between \$18/MWh and \$44/MWh, GenCo-1 allocates 19.60MW to LSE-1. Note that ISO allows a maximum of 19.60MW for non-local bilateral transaction between GenCo-1 and LSE-1. By contrast, Figure 7.2 shows that GenCo-4 does not allocate same power quantity to LSE-3 for all prices in the negotiable price set between \$65.9/MWh and \$91.9/MWh. According to GenCo-4's match making results in Figure 7.2, for any price above \$78.9/MWh, GenCo-4 should allocate 128.0MW to LSE-3. On the other hand, for any price below \$78.9/MWh, GenCo-4 must reduce the power allocation below 128.0MW.

The power allocation results of GenCo-1 and GenCo-4 are different because their trading prices, fuel cost coefficients and local nodes are different. In consequence, their return characteristics of bilateral trades and day-ahead auction are also different. Based on its return characteristics, each GenCo develops its overall utility function with an overall objective of maximizing returns and minimizing risks of its trades. For that reason, the power allocation results of GenCo-1 and GenCo-4, shown in Figure 7.1 and Figure 7.2 respectively, have different characteristics.

GenCo-1's match making finds that for bilateral transaction with LSE-1 at any price in the shown negotiable price set, GenCo-1 gets best overall utility by keeping its power allocation to the bilateral trade fixed at 19.60MW. By contrast, GenCo-4's match making finds that for bilateral transaction with LSE-3 at prices below \$78.9/MWh, GenCo-4 gets best overall utility by reducing its power allocation to the bilateral trade below 128.0MW and allocating the reduced quantity to the day-ahead auction instead.

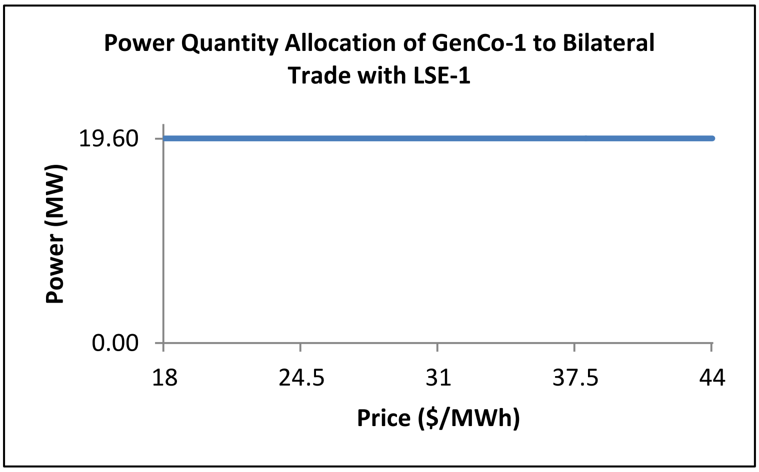

Figure 7.1 Power Quantity Allocation of GenCo-1 to bilateral trade with LSE-1

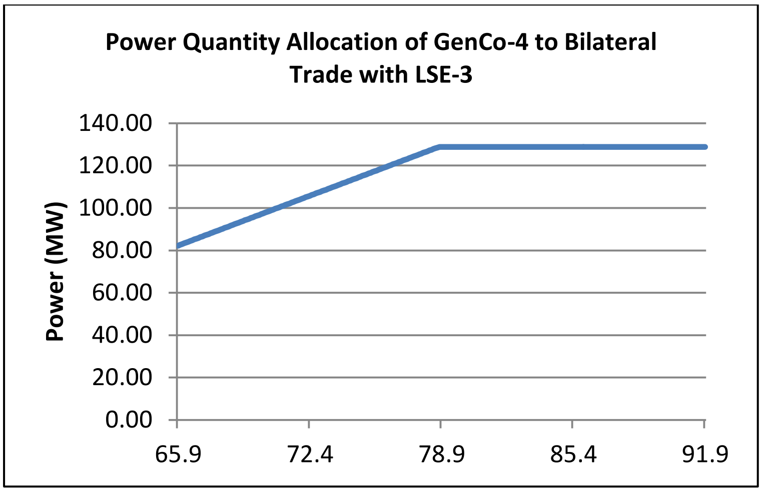

Figure 7.2 Power Quantity Allocation of GenCo-4 to bilateral trade with LSE-3

Figure 7.3 illustrates that GenCo-1's utility of bilateral trade with LSE-1 increases with trading price because the two quantities are directly proportional, as shown in equation (6.33), for negotiable price set between \$18/MWh and \$44/MWh. For the same reason, GenCo-4's utility of bilateral trade with LSE-3 also increases with trading price, as shown in Figure 7.4, for negotiable price set between $65.9/MWh and $91.9/MWh. Despite having the direct proportionately characteristics, the utilities of GenCo-1 and GenCo-4 have different values because their trading prices, fuel cost coefficients and allocated power quantities are different.

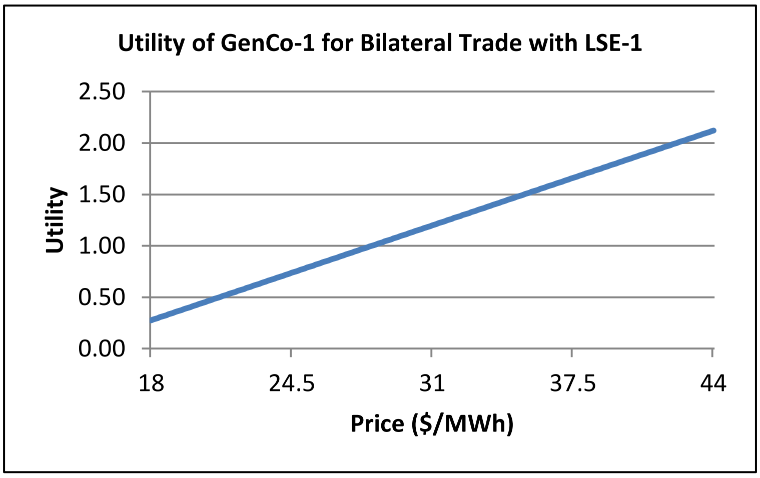

Figure 7.3 Utility of GenCo-1 for bilateral trade with LSE-1

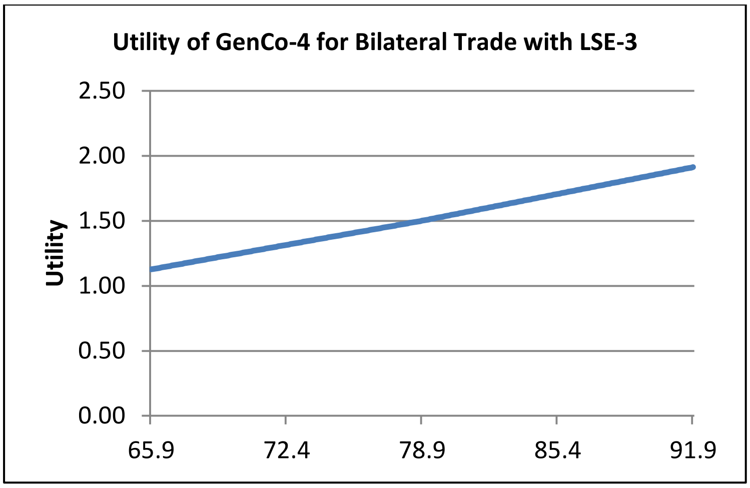

Figure 7.4 Utility of GenCo-4 for bilateral trade with LSE-3

Most power allocation results of LSEs are similar and Figure 7.5 illustrates a typical power allocation result of an LSE. It shows that for any price in the negotiable price set, between $18/MWh and $44/MWh, LSE-1 allocates 19.60MW to GenCo-1. By contrast, Figure 7.6 shows that LSE-3 does not allocate same power to GenCo-4 for all prices in the negotiable price set between \$65.9/MWh and \$91.9/MWh. According to LSE-3's match making results in Figure 7.6, for any price below \$78.9/MWh, LSE-3 should allocate 75.0MW to GenCo-4. However, for any price above \$78.9/MWh, LSE-3 must reduce its power allocation below 75.0MW.

The power allocation results of LSE-1 and LSE-3 are different because their trading prices, flat-rates agreed with end-consumers and local nodes are different. In consequence, their return characteristics of bilateral trades and day-ahead auction are also different. Based on its return characteristics, each LSE develops its overall utility function with an overall objective of maximizing returns and minimizing risks of its trades. For that reason, the power allocation results of LSE-1 and LSE-3, shown in Figure 7.5 and Figure 7.6 respectively, have different characteristics.

LSE-1's match making finds that for bilateral transaction with GenCo-1 at any price in the shown negotiable price set, LSE-1 gets best overall utility by keeping its power allocation to the bilateral trade fixed at 19.60MW. By contrast, LSE-3's match making finds that for bilateral transaction with GenCo-4 at prices above \$78.9/MWh, LSE-3 gets best overall utility by reducing its power allocation to the bilateral trade below 75.0MW and allocating the reduced quantity to the day-ahead auction instead.

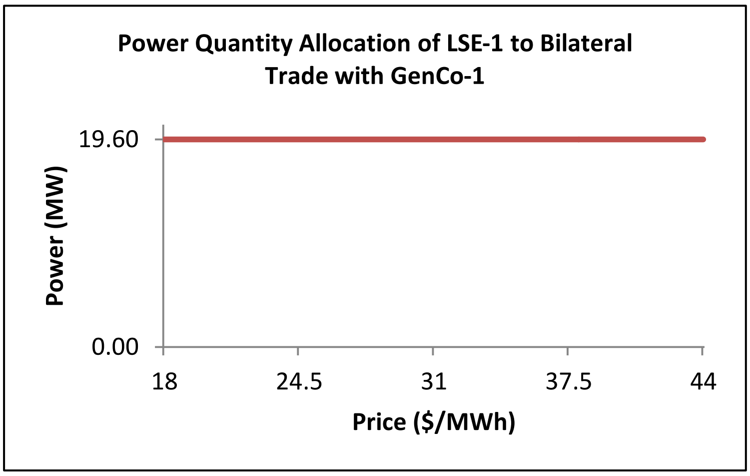

Figure 7.5 Power Quantity Allocation of LSE-1 for Bilateral transaction with GenCo-1

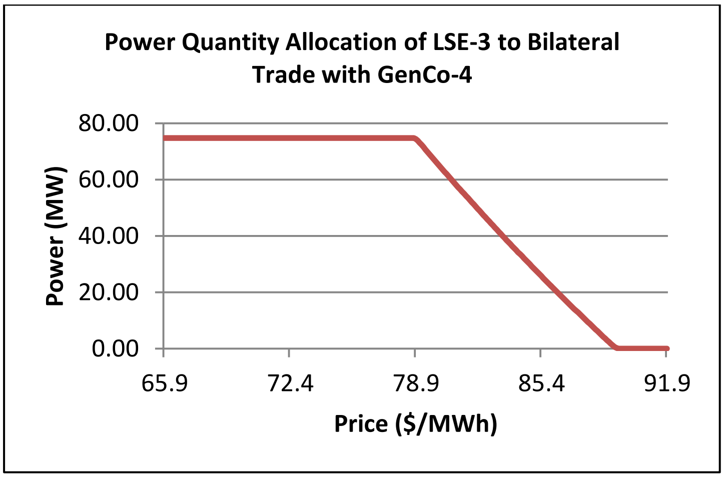

Figure 7.6 Power Quantity Allocation of LSE-3 for Bilateral transaction with GenCo-4

Figure 7.7 illustrates that LSE-1's utility of bilateral trade with GenCo-1 decreases with trading price because the two quantities are inversely proportional, as shown in equation (7.22), for negotiable price set between \$18/MWh and \$44/MWh. For the same reason, LSE-3's utility of bilateral trade with GenCo-4 also decreases with trading price, as shown in Figure 7.8, for negotiable price set between \$65.9/MWh and \$91.9/MWh. Despite having the inverse proportionately characteristics, the utilities of LSE-1 and LSE-3 have different values because their trading prices, flat-rates agreed with end-consumers and allocated power quantities are different.

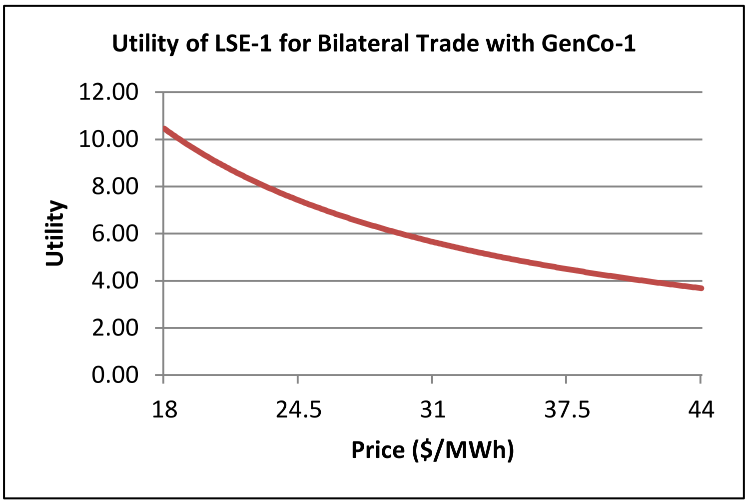

Figure 7.7 Utility of LSE-1 for Bilateral transaction with GenCo-1

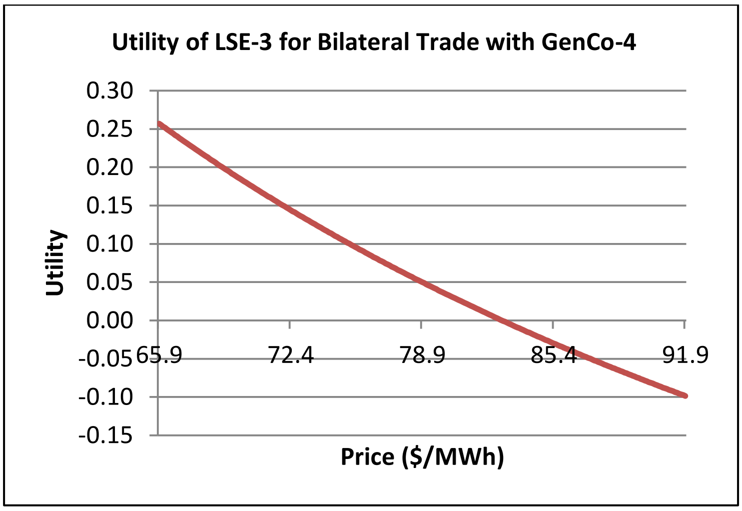

Figure 7.8 Utility of LSE-3 for Bilateral transaction with GenCo-4

7.5 Conclusions

Compared to previous match making models for bilateral transactions, this Chapter has contributed to knowledge by presenting mathematical details of new match making algorithms for direct-search bilateral transactions. Match making is achieved by direct-search without any organized bulletin-board/broker or match making organizer. Furthermore, instead of random match making, portfolio optimization based match making systematically explores available electricity trading options, over the entire range of negotiable prices and throughout the market. Depending on private profit-seeking goals, risk-aversion preferences and market history, each GenCo and LSE individually finds its match making results. The new match making algorithms for both GenCo and LSE are incorporated in FABS.

Market participants use match making algorithms to discover, by direct-search in a deregulated wholesale electricity market, suitable partners for bilateral transaction. Market participants also determine quantities and utilities of power allocations for bilateral transaction over a set of negotiable prices. Depending on its private data like fuel cost coefficients, a GenCo may have to shift its power allocation, for prices in lower half of the negotiable price set, from a bilateral trade to the day-ahead auction for achieving best overall utility of its trading portfolio. On the contrary, for prices in upper half of the negotiable price set, an LSE may have to shift its power allocation from a bilateral trade to the day-ahead auction for achieving the same objective in view of its private data like flat-rate agreed with end-consumers. Utility of a GenCo is directly proportional to bilateral transaction price that it gets from an LSE. Conversely, utility of an LSE is inversely proportional to bilateral transaction price that it pays to a GenCo. Since match making determines power quantities and trading utilities of possible bilateral trades, for all prices in the negotiable price sets, market participants use the data for bilateral negotiations.

7.6 References

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8 Simulation of Utility based Bilateral Negotiation Strategy supported by Bayesian Learning

8.1 Introduction

This chapter describes how bilateral negotiation is achieved between GenCos and LSEs, in FABS - “Financial transmission instruments, energy Auction and Bilateral transaction Simulator for wholesale electricity markets”. All market participants have to agree on a bilateral transaction protocol prior to negotiation but every market participant can have a private strategy during negotiation rounds. An LSE develops its trading utility based negotiation strategy by using results of its match making algorithm, presented in the previous Chapter. Similarly, based on its match making algorithm in the previous Chapter, a GenCo develops its trading utility based negotiation strategy. In addition, a GenCo is enabled to support its trading utility based strategy by learning from interaction with negotiating partner and adapting its behaviour accordingly. Each market participant individually develops its negotiation strategy to fulfil private profit-seeking goals and risk-aversion preferences.

In practical electricity markets, participants engage in multi-round bilateral negotiations and make gradual financial concessions in successive rounds to secure medium-duration bilateral transactions. Market participants take into account effects of historic prices in organized markets on future bilateral transactions. They need to consider the characteristics of market prices because they use bilateral transactions as hedge against uncertainty of the prices. Market participants have incomplete information about private profit-seeking goals and risk-aversion preferences of others. However, they can discover some information about others from responses during multi-round bilateral negotiations and must learn and adapt to dynamic scenarios. Characteristics of practical bilateral negotiations, described in this paragraph, will act as suitability criterion of simulation techniques for bilateral negotiations, reported in literature and discussed as follows.

Since a detailed literature review of simulation techniques for bilateral negotiation was presented in Chapter 3, only a summary is provided here. Heuristic as well as learning techniques are reported in literature for simulation of bilateral negotiations. Heuristic techniques are derived from human attitudes, including time-dependent and behaviour-dependent strategies, during practical negotiations. Agents using time-dependent or behaviour-dependent strategies make financial concessions to each other in successive rounds that depend on remaining time or opponent behaviour respectively. Heuristic techniques are used for simulation of bilateral negotiation in a large number of papers including [1], [2], [3], [4], [5] and [6]. If negotiating agents only depend on their behaviour-dependent strategies and resort to contending behaviour then there is risk that agent positions may not converge and consequently bilateral negotiation may fail. However, time-dependent strategy is a simple method that can lead to successful bilateral negotiations. In [7] and [8] time-dependent strategy is combined with an assumed measure of bilateral transaction reward that depends on energy prices in a specific price range.

A wide variety of learning techniques are used for simulation of bilateral negotiations, including single-agent reinforcement learning, multi-agent reinforcement learning and supervised learning. In reinforcement learning, if an action leads to favourable results then tendency to implement that action should be reinforced, otherwise the tendency should be reduced [9]. Single-agent reinforcement learning technique assumes that the agent environment remains stationary because this technique is based on the Markov decision process. The assumption of stationary environment does not remain valid in the case of reinforcement learning in a multi-agent system because an agent's environment contains other autonomous agents that are able to learn and adapt. Unlike single-agent reinforcement learning, multi-agent reinforcement learning techniques take into account dynamic nature of an agent's environment. In supervised learning, an agent generally learns from examples in a set of training inputs and outputs provided by an intelligent supervisor. However, a supervised learning agent can also learn about other agents in the environment by repeated interactions with them. A literature review of single-agent reinforcement learning, multi-agent reinforcement learning and supervised learning is presented in the following three paragraphs respectively.

Applications of Q-learning, a particular type of single-agent reinforcement learning, are reported in [10], [11] and [12]. These applications either do not consider dynamics of historic prices in organized markets on subsequent negotiations or do not model multi-round bilateral negotiations that can lead to medium-duration bilateral transactions. Moreover, uses of single-agent reinforcement learning in multi-agent systems do not have solid theoretical foundations because of assuming a stationary environment.

Multi-agent reinforcement learning falls into three categories (i) agent-independent, (ii) agent-aware and (iii) agent-tracking methods. Agent-independent methods use game-theoretic solvers that need complete information about all agents. Agent-aware methods use heuristics to adapt to other agents but carry a risk of non-convergence resulting in failure of negotiation. Agent-tracking methods estimate dynamic policies of other agents and adapt some kind of best response to the estimated policies [13]. Among the three multi-agent reinforcement learning methods, agent-tracking approach has potential to avoid non-convergence as well as lead to successful bilateral negotiations between agents that have incomplete information about each other.

An agent can estimate types or intentions of its opponents in bilateral negotiations by supervised learning. Bayesian classification, a particular type of supervised learning, is used in [7] and [8] to classify opponent behaviour in multi-round *bilateral negotiations*. Bayesian learning, another kind of supervised learning, can estimate private intentions of opponents from information revealed through interactions during bilateral negotiations. In [14] and [15], Bayesian learning is used to estimate the price that opponent is likely to propose in the last round of bilateral negotiation. This thesis uses the Bayesian learning method of [14], presented in Appendix B. Bayesian learning can play an auxiliary role by supporting a main negotiation strategy.

Instead of using an assumed measure of reward like [7] and [8], this Chapter introduces a new way, based on utility results over a specified price set, of measuring reward of a bilateral transaction option. Moreover, every market participant has to rely on its perception of available negotiation time because it is not sure about private intentions of others. The trading reward and the perception of available negotiation time are combined to develop a main negotiation strategy termed utility based strategy. Furthermore, Bayesian learning is used to estimate the price that opponent is likely to propose in the last perceived round of bilateral negotiation. Bayesian learning is followed by a new method of adapting the main utility based strategy in response to opponent behaviour. Since Bayesian learning is followed by an appropriate response to opponent, the combination attains capabilities of agent-tracking approach, in multi-agent reinforcement learning.

The rest of the chapter is organized as follows. Section 8.2 describes bilateral transaction protocol used by market participants. Section 8.3 and Section 8.4 present utility based negotiation strategies of a Load Serving Entity and a Generation Company respectively. Section 8.5 outlines utility and Bayesian learning based strategy of a Generation Company. Case studies and results are presented in Section 8.6 and Section 8.8 respectively, whereas Section 8.8 concludes this Chapter.

8.2 Bilateral Transactions Protocol

As discussed in Chapter 7, a bilateral transaction protocol is anticipated to have become an industry wide standard, even in a decentralized market scenario. Such a uniform protocol avoids haphazard behaviour by participants and facilitates smooth functioning of bilateral transaction processes. In modern electricity markets of North America, annual Financial Transmission Rights auction follows a pre announced calendar. In view of that, it is assumed that participants undertake match making after ISO announces results of annual Financial Transmission Rights auction, in FABS. Match making is an individual decision making process that is completed by all market participants on the same day as announcement of the results.

FABS also assumes that after announcing the auction results, independent system operator leaves a period of ten working days before annual FTRs come into effect. Participants use these ten working days to engage in negotiation negotiations that can extend up to five rounds of two working days each. For bilateral negotiation between a GenCo and an LSE, the LSE initiates a round by sending an energy bid to the GenCo on first day of the round. The GenCo responds on the following day by sending an energy offer to the LSE. The LSE and GenCo continue bilateral negotiation until they agree, either one quits negotiation or they fail to reach an agreement in the five rounds.

During bilateral negotiations, market participants can only exchange offer or bid prices in their *negotiable price sets*. A market participant's *negotiable price sets* contain a *negotiable price set* for each of its bilateral transaction options. As explained in Chapter 7 for match making, a market participant determines its *negotiable price sets* that conform to the first three rules of the bilateral transaction protocol, presented in this section. The remaining eight rules, from 4 to 11, of the protocol exclusively deal with bilateral negotiations that are described in this Chapter. It is assumed that the bilateral transaction protocol contains following rules that have already been discussed, are self-explanatory or will become clear by discussion in the rest of the Chapter.

1. Expectation of LMP at a GenCo node acts as *reference price* for bilateral negotiation between the GenCo and LSEs.
2. Participants can propose prices that only deviate up to a certain extent, termed *price deviation*, from the *reference price*.
3. A valid *negotiable price set* is a set of discrete prices at *price intervals* of \$0.1/MWh.
4. Bilateral transactions can be agreed for a minimum of 10MW quantity of power. It is assumed that bilateral transactions for less than 10MW are not worth resources exhausted in securing the transactions.
5. LSEs start negotiation process in the first round
6. Negotiation process has to be completed in a maximum of ten working days

7. Negotiation process can extend up to a maximum of five rounds of two working days each. However, a participant may privately choose a shorter negotiation time than five rounds.
8. Unless a participant has exhausted its private negotiation time, it follows deadline of next working day to respond to each proposal of energy price and power quantity.
9. LSEs can hold on to their price bids in the previous round but cannot decrease their price bids in the next round.
10. GenCos can hold on to their price offers in the previous round but cannot increase their price offers in the next round.
11. Unless a participant agrees or quits in earlier rounds, GenCos end negotiation process in the fifth round.

8.3 Utility based Negotiation Strategy of a Load Serving Entity

With match making algorithm, presented in Chapter 7, each LSE determines power quantities and trading utilities of its bilateral transaction options over *negotiable price sets*. This section explains how an LSE uses the results of match making algorithm to develop a utility-based strategy for multi-round bilateral negotiation.

Description of the utility based strategy's mathematical model for LSE is detailed in subsections 8.3.1 to 8.3.4. A brief outline of contents covered in each of these subsections is provided here. Based on its match making results, an LSE privately selects strategic price sets for bilateral negotiations with GenCos, as explained in Section 8.3.1. LSE decides that only the prices in strategic price set for a GenCo can be submitted as price bids to the GenCo. In Section 8.3.2, using strategic price set for a GenCo and utility results for prices in the set, LSE determines total strategic reward as a measure of its stake during multi-round bilateral negotiation with the GenCo. LSE makes compromises in successive rounds, to make negotiations a success, by deciding how much of the total strategic reward must me retained in a particular round, as explained in Section 8.3.3. Section 8.3.4 explains how an LSE uses retained strategic reward value to select its price bid to a GenCo in each round.

LSE's negotiation algorithm for the utility based strategy is presented in Section 8.3.5. An overview of steps in the negotiation algorithm is provided here. In step 1 of the algorithm, LSE calculates and stores total strategic reward as well as retained strategic reward at each price in its strategic price set. LSE needs the stored strategic reward results in all negotiation rounds. In step 2, LSE sets current round to the first round of bilateral negotiation. Step 3 consists of LSE's actions while negotiation rounds are in progress. LSE carries out step 3-a for each GenCo before moving to the next round in step 3-b. In steps 3-a-i to 3-a-iv, LSE determines bid suggested by its own strategy for a GenCo. In step 3-a-v, LSE compares price bid suggested by its strategy with price offer received from the GenCo. If the self-suggested price bid is less than the received price offer then LSE submits strategic price bid to the GenCo and receives GenCo's response. Otherwise, LSE accepts the GenCo's offer, as shown in step 3-a-vi.

8.3.1 Strategic Price Sets

During bilateral negotiation, an LSE's energy price bids must lie within publicly known *negotiable price sets* that conform to the bilateral transaction protocol. In addition, the transaction protocol does not allow bilateral transactions of less than 10MW. It is assumed that bilateral transactions for less than 10MW are not worth resources required for securing the transactions. Although an LSE has match making power allocation results over *negotiable price sets*, the allocated power quantities may not be more than or equal to 10MW over the entire sets. Therefore, an LSE privately determines price sets over which its allocated power quantities are more than or equal to 10MW. An LSE only chooses energy price bids from its privately determined price sets, termed *strategic price sets*, by using a utility-based bilateral negotiation strategy.

Negotiable price sets, used in match making algorithm, contain discrete prices at *price intervals* of \$0.1/MWh. Consequently, power allocation and trading utility results of match making algorithm are available as discrete data at *price intervals* of

$0.1/MWh, over *negotiable price sets*. LSEs' power and utility results were presented in Chapter 7 as continuous line graphs for simplicity. Nevertheless, if an LSE's discrete power allocation and trading utility data is visualized as bar graphs then it is easier to understand utility-based negotiation strategy developed in this Chapter. Although data of actual results is available at *price intervals* of $0.1/MWh, an LSE's hypothesized power and utility data for bilateral transaction with a GenCo, illustrated in Figure 8.1 and Figure 8.2 respectively, uses *price intervals* of $1/MWh for brevity.

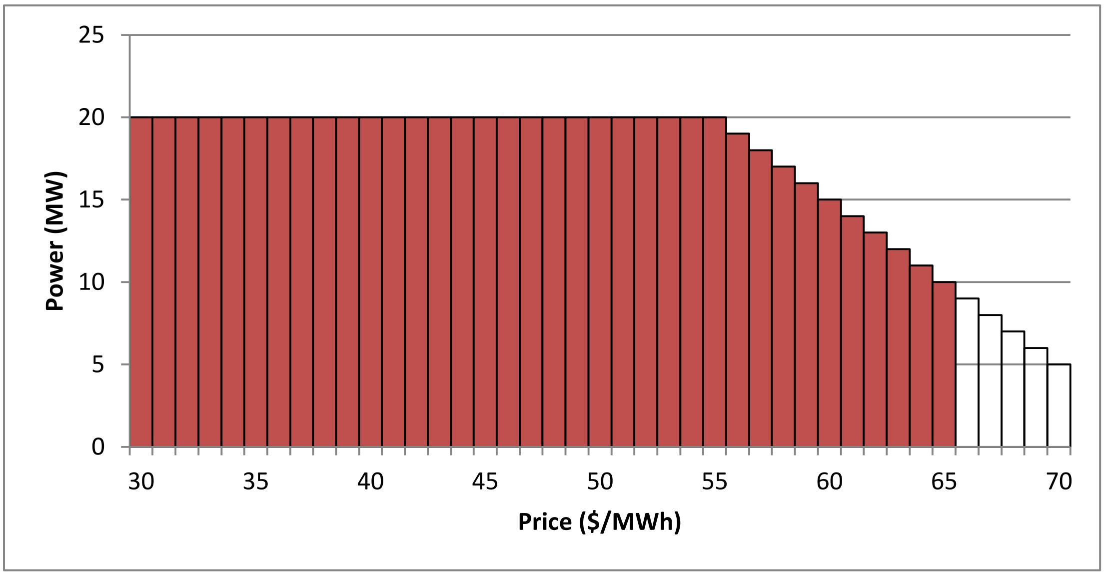

Figure 8.1 Hypothesised data of power allocated by an LSE for bilateral transaction with a GenCo

LSE *l*'s hypothesized power allocation results for bilateral transaction with GenCo *g* are shown in Figure 8.1. The hypothesized results are shown over the negotiable price set, equally extending on both sides of the $50/MWh *reference price*, from $30/MWh to $70/MWh. The results assume that LSE *l*'s match making algorithm allocates 20MWh to the bilateral trade with GenCo *g* for prices lower than or equal to $55/MWh. Furthermore, the power quantity allocation gradually decreases from 20MWh to 5MWh as price increases from $55/MWh to $70/MWh.

An LSE uses its power allocation results for bilateral transaction with a GenCo to graphically find its *strategic price set*, as explained next. According to the transaction protocol, minimum acceptable quantity of a bilateral transaction is 10MW. In Figure 8.1, power allocation is above 10MW between \$30/MWh and \$65/MWh. However, it falls below 10MW at \$65/MWh price and remains so up to \$70/MWh. Therefore, LSE l selects \$65/MWh as its *maximum strategic price* for bilateral transaction with GenCo g, $sp_{g,\max}^{l}$. In addition, LSE l selects \$30/MWh as its *minimum strategic price* for bilateral transaction with GenCo g, $sp_{g,\min}^{l}$, because it would like to buy energy at lowest feasible price. Figure 8.1 covers entire negotiable price set but its bar graphs are shown filled for only *strategic price set*, from \$30/MWh to \$65/MWh.

Knowing the *minimum strategic price*, $sp_{g,\min}^{l}$, the *maximum strategic price*, $sp_{g,\max}^{l}$, and the *price interval*, $\Delta\pi$, LSE l's private *strategic price set* for bilateral transaction with GenCo g, S_{g}^{l}, is expressed as,

$$S_{g}^{l} = \left\{ sp_{g,\min}^{l} + p\Delta\pi : p = 0,1,\ldots,\frac{sp_{g,\max}^{l} - sp_{g,\min}^{l}}{\Delta\pi} \right\} \tag{8.1}$$

8.3.2 Total Strategic Reward

Using strategic price set for a GenCo and utility results for prices in the set, LSE determines total strategic reward as a measure of its stake during multi-round bilateral negotiation with the GenCo. LSE l's hypothesized trading utility results for bilateral transaction with GenCo g are shown in Figure 8.2, for entire negotiable price set. The hypothesized results illustrate that utility gradually decreases from approximately 2.5 to 1.0 as price increases from \$30/MWh to \$70/MWh. Since LSE uses utility-based bilateral negotiation strategy to offer prices within its *strategic price set*, it should only consider the change in bilateral transaction utility that occurs over the *strategic price set*, shown as filled portion of bar graphs between \$30/MWh and \$65/MWh.

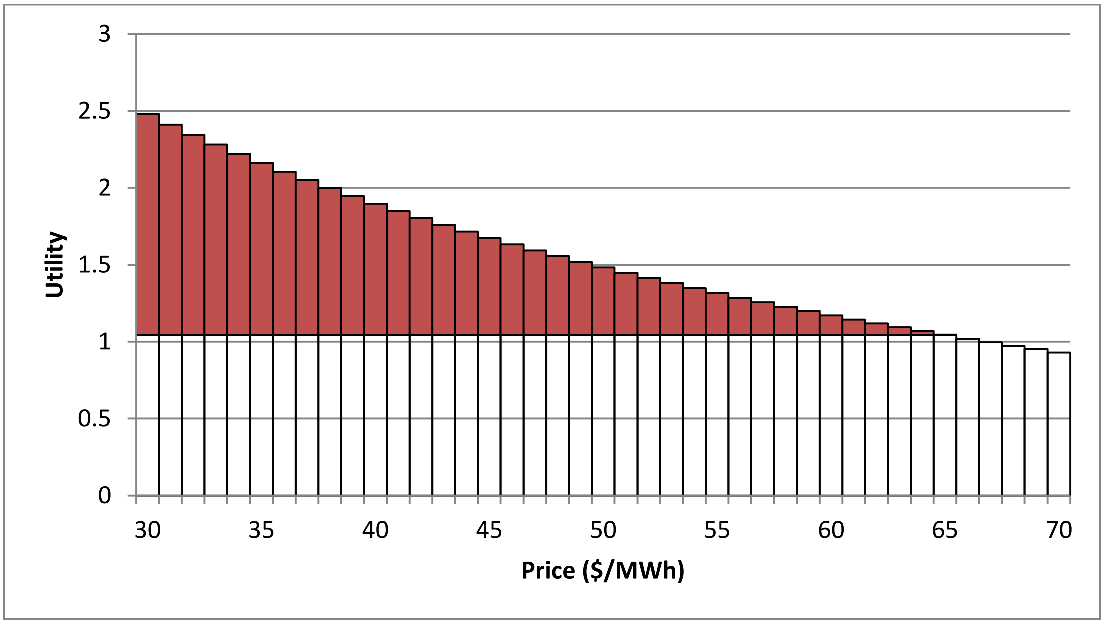

Figure 8.2 Hypothesized data of utility determined by an LSE for bilateral transaction with a GenCo

In this thesis, an LSE's total strategic reward of a bilateral trade is defined as reward that can be obtained by LSE if it secures the bilateral transaction at *minimum strategic price*. In other words, the total strategic reward is at stake during multi-round bilateral negotiation. It is critical to note that, even if LSE pays *maximum strategic price* to avoid failure of negotiation then, despite losing total strategic reward, it secures a bilateral transaction that is recommended by portfolio optimization due to its utility. The total strategic reward of LSE l for bilateral transaction with GenCo g , $Q^l_{g,TOTAL}$, represented by filled area in Figure 8.2, is calculated as,

$$Q^l_{g,TOTAL} = \sum_{\pi = sp^l_{g,\min}}^{sp^l_{g,\max}} \left\{ U^l_g(\pi) - U^l_g\left(sp^l_{g,\max}\right) \right\} \Delta\pi \qquad (8.2)$$

where $U^l_g\left(sp^l_{g,\max}\right)$ is utility at maximum strategic price, $U^l_g(\pi)$ is utility at price π that varies with *price interval* $\Delta\pi$ over *strategic price set*. As discussed in Chapter 7, utility of a risky non-local bilateral trade and a risk-free local bilateral trade is calculated by equation (7.22) and equation (7.24) respectively.

Above described method of calculating total strategic reward in FABS is compared with another way [7] of estimating bilateral transaction reward. Development of equation (8.2) follows a graphical description of involved quantities but [7] does not offer any graphical insights. Moreover, although equation (8.2) for total strategic reward in FABS has similarity with the equation for estimated bilateral transaction reward in [7], the two equations are essentially different because (8.2) incorporates trading utility instead of price. In [7] total assumed reward only depends on energy prices in strategic price set whereas, considering quantities used in equation (7.22) and equation (7.24), in FABS total strategic reward also depends on optimal power quantity allocations to LSEs at energy prices in the set, flat-rate agreed with the end-consumers at local node of LSE, Financial Transmission Rights held by LSE between its local node and GenCo nodes i and j as well as expectations, variances and covariances of LMPs at transmission system nodes. Therefore, total strategic reward, used in FABS, is a better measure of bilateral transaction reward as compared to total assumed reward used in [7].

8.3.3 Retained Strategic Reward

LSE makes compromises in successive rounds, to make negotiations a success, by deciding how much of the total strategic reward must me retained in a particular round. If LSE insists on an extreme stance of obtaining its total strategic reward then it bids *minimum strategic price* in each round. However, if GenCo is not willing to accept *minimum strategic price* bid of LSE then bilateral negotiation fails. On the other extreme, if LSE relinquishes its total strategic reward then it bids *maximum strategic price* in each round. In such case, LSE may succeed in bilateral negotiations but at the cost of losing its total strategic reward. In practice, bilateral negotiation typically involves a number of rounds of concessionary price bids by LSE l and concessionary price offers by GenCo g. LSE l has a private limit on the maximum number of rounds for bilateral negotiation, T^l, and if it fails to reach a bilateral agreement by round T^l then it withdraws from negotiation. Since LSE l does not have access to GenCo g's private limit on the maximum number of rounds, it does not know the maximum number of rounds that can possibly take place between the two of them. Based on its own private limit, T^l, and current negotiation round, *t*, LSE *l* perceives that remaining negotiation time is $1-t/T^l$.

LSE tries to secure a bilateral transaction by the end of its time limit while attempting to retain maximum possible strategic reward in each round. LSE calculates its retained strategic reward in round *t*, $Q^l_{g,retained}(t)$, as a fraction of its total strategic reward, $Q^l_{g,TOTAL}$, that is directly proportional to its perception of remaining negotiation time in round *t*, $1-t/T^l$, by

$$Q^l_{g,retained}(t) = \left(1-t/T^l\right) Q^l_{g,TOTAL} \tag{8.3}$$

8.3.4 Strategic Price and Quantity Bid

An LSE uses retained strategic reward value to select its price bid to a GenCo in each round. An LSE can find strategic price bid in round *t*, $sp_g^{l,bid}(t)$, corresponding to retained strategic reward in round *t*, $Q^l_{g,retained}(t)$, if it knows a general mathematical relationship between a price, sp^l_g, in strategic price set, S^l_g, and retained strategic reward at that price, $Q^l_{g,retained}\left(sp^l_g\right)$. By rewriting equation (8.2), relationship between a price sp^l_g and retained strategic reward at the price, $Q^l_{g,retained}\left(sp^l_g\right)$, is expressed as,

$$Q^l_{g,retained}\left(sp^l_g\right) = \sum_{\pi = sp^l_g}^{sp^l_{g,\max}} \left\{U^l_g(\pi) - U^l_g\left(sp^l_{g,\max}\right)\right\}\Delta\pi \tag{8.4}$$

Using equation (8.4), LSE *l* calculates $Q^l_{g,retained}\left(sp^l_g\right)$ for each price sp^l_g in the strategic price set, S^l_g, and stores the calculated values in a table that is consulted in each negotiation round. In the table, LSE *l* looks up the price sp^l_g at which stored value of retained strategic reward, $Q^l_{g,retained}\left(sp^l_g\right)$, equals or most closely approximates retained strategic reward for round *t*, $Q^l_{g,retained}(t)$, calculated from equation (8.3). Consequently, LSE l selects the price sp_g^l as its strategic price bid to GenCo g in round t, $sp_g^{l,bid}(t)$. After choosing the strategic price bid, $sp_g^{l,bid}(t)$, LSE l looks up its power allocation results, like hypothesized results shown in Figure 8.1, and selects power quantity corresponding to the chosen price as its strategic quantity bid for bilateral transaction with GenCo g in round t, $sq_g^{l,bid}(t)$.

Based on transaction protocol discussed in Section 8.2 and mathematical model presented in this section, an LSE's negotiation algorithm for utility based strategy is shown in Section 8.3.5. The step by step algorithm conforms to the protocol and refers to equations developed during discussion of utility based strategy's mathematical model. Moreover, a summary of steps in the negotiation algorithm was provided at the beginning of Section 8.3.

8.3.5 Negotiation Algorithm

1) **For** each GenCo g **Do**
   a) Evaluate total strategic reward, $Q_{g,TOTAL}^l$, by (8.2).
   b) Using equation (8.4), calculate $Q_{g,retained}^l\left(sp_g^l\right)$ for each price sp_g^l in the *strategic price set* S_g^l and store the calculated values in a look-up table.
2) Set round to one ($t=1$)
3) **While** round <= maximum rounds ($t \le T^l$) **Do**
   a) **For** each GenCo g **Do**
      i) Compute retained strategic reward $Q_{g,retained}^l(t)$ by (8.3).
      ii) In the look-up table, find price sp_g^l at which stored value of retained strategic reward, $Q_{g,retained}^l\left(sp_g^l\right)$, equals retained strategic reward for round t, $Q_{g,retained}^l(t)$
      iii) Choose sp_g^l as strategic price bid $sp_g^{l,bid}(t)$, for purchase of energy.
      iv) Determine strategic quantity bid $sq_g^{l,bid}(t)$, corresponding to the strategic price bid $sp_g^{l,bid}(t)$, for purchase of energy.

v) **If** it is round one ($t = 1$) **Or** strategic price bid < strategic price offer $\left(sp_g^{l,bid}(t) > sp_l^{g,offer}(t-1)\right)$ **Then**

(1) Convey strategic quantity bid $sq_g^{l,bid}(t)$, and strategic price bid $sp_g^{l,bid}(t)$,to GenCo *g*.

(2) From GenCo *g*, receive strategic price offer $sp_l^{g,offer}(t)$ and strategic quantity offer $sq_l^{g,offer}(t)$.

vi) Else

(1) agreed price = strategic price offer $\left(ap_g^l = sp_l^{g,offer}(t-1)\right)$ and agreed quantity = strategic quantity offer $\left(aq_g^l = sq_l^{g,offer}(t-1)\right)$

(2) Convey agreed price ap_g^l and agreed quantity aq_g^l for purchase of energy to GenCo *g*.

b) Increment round by one ($t = t+1$).

8.4 Utility based Negotiation Strategy of a Generation Company

With match making algorithm, presented in Chapter 7, each GenCo determines power quantities and trading utilities of its bilateral transaction options over negotiable price sets. This section explains how a GenCo uses the results of match making algorithm to develop a utility-based strategy for multi-round bilateral negotiation.

Description of the utility based strategy's mathematical model for GenCo is detailed in subsections 8.4.1 to 8.4.4. A brief outline of contents covered in each of these subsections is provided here. Based on its match making results, a GenCo privately selects strategic price sets for bilateral negotiations with LSEs, as explained in Section 8.4.1. GenCo decides that only the prices in strategic price set for an LSE can be submitted as price bids to the LSE. In Section 8.4.2, using strategic price set for an LSE and utility results for prices in the set, GenCo determines total strategic reward as a measure of its stake during multi-round bilateral negotiation with the

LSE. GenCo makes compromises in successive rounds, to make negotiations a success, by deciding how much of the total strategic reward must me retained in a particular round, as explained in Section 8.4.3. Section 8.4.4 explains how a GenCo uses retained strategic reward value to select its price offer to an LSE in each round.

GenCo's negotiation algorithm for the utility based strategy is presented in Section 8.4.5. An overview of steps in the negotiation algorithm is provided here. In step 1 of the algorithm, GenCo calculates and stores total strategic reward as well as retained strategic reward at each price in its strategic price set. GenCo needs the stored strategic reward results in all negotiation rounds. In step 2, GenCo sets current round to the first round of bilateral negotiation. Step 3 consists of GenCo's actions while negotiation rounds are in progress. GenCo carries out step 3-a for each LSE before moving to the next round in step 3-b. In step 3-a-i GenCo receives bid from an LSE. In steps 3-a-ii to 3-a-v, GenCo determines offer suggested by its own strategy for the LSE. In step 3-a-vi, GenCo compares the price offer suggested by its strategy with price bid received from the LSE. If the self-suggested price offer is less than the received price bid then GenCo accepts the bid. Otherwise, GenCo submits strategic price offer to the LSE, as shown in step 3-a-vii.

8.4.1 Strategic Price Sets

During bilateral negotiation, a GenCo's offer prices must lie within publicly known *negotiable price sets* specified by bilateral transaction protocol. In addition, the transaction protocol does not allow bilateral transactions of less than 10MW. It is assumed that bilateral transactions for less than 10MW are not worth resources required for securing the transactions. Although a GenCo has match making power allocation results over *negotiable price sets*, the allocated power quantities may not be more than 10MW over the entire sets. Therefore, a GenCo privately determines price sets over which its allocated power quantities are more than or equal to 10MW. A GenCo only offers energy prices from its privately determined price sets, termed *strategic price sets*, by using a utility-based bilateral negotiation strategy.

Negotiable price sets, used in match making algorithm, contain discrete prices at *price intervals* of \$0.1/MWh. Consequently, power allocation and trading utility results of match making algorithm are available as discrete data, at *price intervals* of \$0.1/MWh, over negotiable price set. GenCos' power and utility results were presented in Chapter 7 as continuous line graphs for simplicity. Nevertheless, if a GenCo's discrete power allocation and trading utility data is visualized as discrete bar graphs then it is easier to understand utility-based negotiation strategy developed in this Chapter. Although data of actual results is available at *price intervals* of \$0.1/MWh, a GenCo's hypothesized power and utility data for bilateral transaction with an LSE, illustrated in Figure 8.3 and Figure 8.4 respectively, uses *price intervals* of \$1/MWh for brevity.

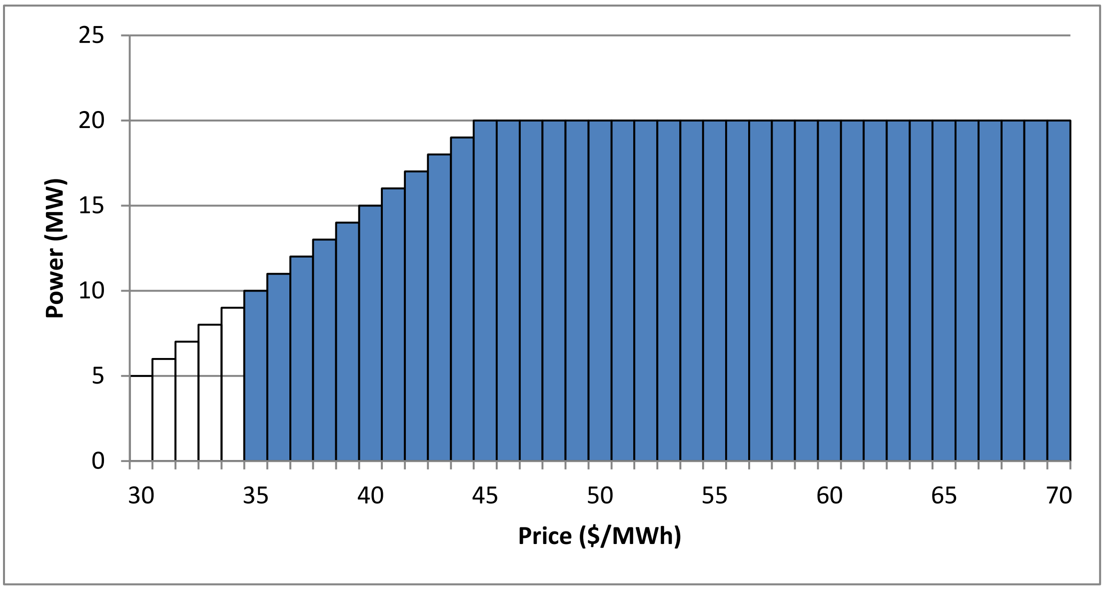

Figure 8.3 Hypothesized data of power allocated by a GenCo for bilateral transaction with an LSE

GenCo *g*'s hypothesized power allocation results for bilateral transaction with LSE *l* are shown in Figure 8.3. The hypothesized results are shown over the negotiable price set, equally extending on both sides of the \$50/MWh *reference price*, from \$30/MWh to \$70/MWh. The results assume that GenCo *g*'s match making algorithm allocates 20MWh to the bilateral trade with LSE *l* for prices higher than or equal to \$45/MWh. Furthermore, the power quantity allocation gradually decreases from 20MWh to 5MWh as price decreases from \$45/MWh to \$30/MWh.

A GenCo uses its power allocation results for bilateral transaction with an LSE to graphically find its strategic price set, as explained next. According to the transaction protocol, minimum acceptable quantity of a bilateral transaction is 10MW. In Figure 8.3, power allocation falls below the minimum quantity at \$35/MWh price. Therefore, GenCo *g* selects \$35/MWh as its *minimum strategic price* for bilateral transaction with LSE *l*, $sp^g_{l,\min}$. In addition, GenCo *g* selects \$70/MWh as its *maximum strategic price* for bilateral transaction with LSE *l*, $sp^g_{l,\max}$, because it would like to get highest possible price for selling its energy. Figure 8.3 covers entire negotiable price set but its bar graphs are shown filled for only *strategic price set*, from \$35/MWh to \$70/MWh.

Knowing the *minimum strategic price*, $sp^g_{l,\min}$, the *maximum strategic price*, $sp^g_{l,\max}$, and the *price interval*, $\Delta\pi$, GenCo *g*'s private *strategic price set* for bilateral transaction with LSE *l*, S^g_l, is expressed as,

$$S^g_l = \left\{ sp^g_{l,\min} + p\Delta\pi : p = 0,1,\ldots,\frac{sp^g_{l,\max} - sp^g_{l,\min}}{\Delta\pi} \right\} \tag{8.5}$$

8.4.2 Total Strategic Reward

Using strategic price set for an LSE and utility results for prices in the set, GenCo determines total strategic reward as a measure of its stake during multi-round bilateral negotiation with the LSE. GenCo *g*'s hypothesized trading utility results for bilateral transaction with LSE *l* are shown in Figure 8.4, for entire negotiable price set. The hypothesized results illustrate that utility gradually increases from 0.5 to 2.5 as price increases from \$30/MWh to \$70/MWh. Since GenCo uses utility-based bilateral negotiation strategy to offer prices within *strategic price set*, it should consider bilateral transaction utility results in the strategic price set only. As a result, Figure 8.4 only shows filled bar graphs between \$35/MWh and \$70/MWh.

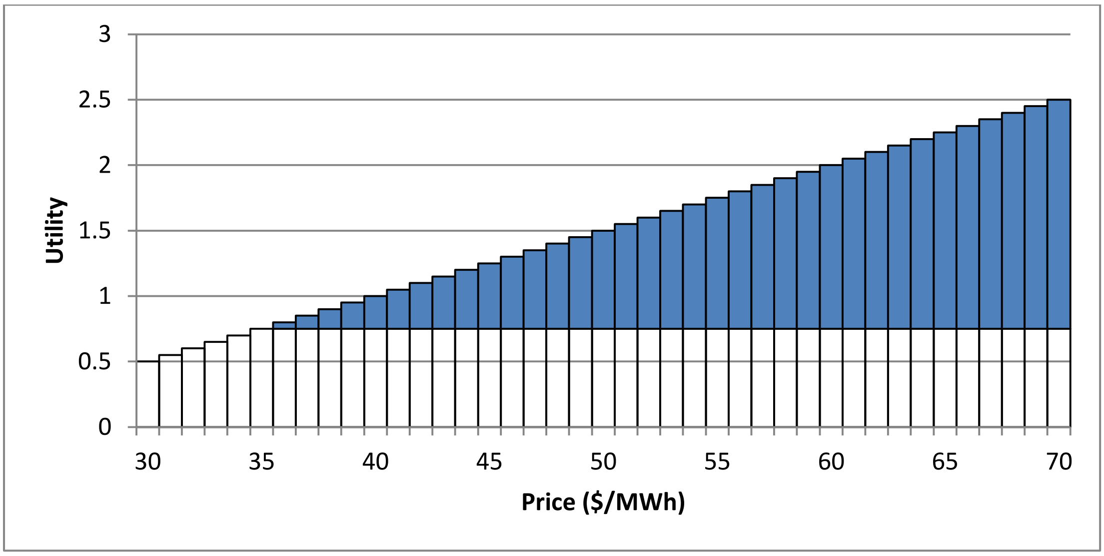

Figure 8.4 Hypothesized data of utility determined by a GenCo for bilateral transaction with an LSE

In this thesis, a GenCo's total strategic reward of a bilateral trade is defined as reward that can be obtained by GenCo if it secures the bilateral transaction at *maximum strategic price*. In other words, the total strategic reward is at stake during multi-round bilateral negotiation. Note that, even if GenCo has to accept *minimum strategic price* to avoid failure of negotiation then, despite losing total strategic reward, it secures a bilateral transaction that is recommended by portfolio optimization because of its utility. The total strategic reward of GenCo g for bilateral transaction with LSE l, $Q^{g}_{l,TOTAL}$, represented by area of filled bars in Figure 8.4, is calculated as,

$$Q^{g}_{l,TOTAL} = \sum_{\pi = sp^{g}_{l,\min}}^{sp^{g}_{l,\max}} \left\{ U^{g}_{l}(\pi) - U^{g}_{l}\left(sp^{g}_{l,\min}\right) \right\} \Delta\pi \qquad (8.6)$$

where $U^{g}_{l}\left(sp^{g}_{l,\min}\right)$ is utility at minimum strategic price, $U^{g}_{l}(\pi)$ is utility at price π that varies with *price interval* $\Delta\pi$ over *strategic price set*. As already discussed in case of LSE in Section 8.3.2, equation (8.6) for GenCo is also different from respective equation in [7]. Furthermore, note that equation (8.6) for total strategic reward of GenCo g is different from equation (8.2) for total strategic reward of LSE l.

Each term of the summation in equation (8.6) contains GenCo g's utility at *minimum* strategic price, $U_l^g\left(sp_{l,\min}^g\right)$ because that is its minimum utility, as illustrated in Figure 8.4. In contrast, every term in summation of equation (8.2) contains LSE l's utility at *maximum* strategic price, $U_g^l\left(sp_{g,\max}^l\right)$ because that is its minimum strategy, as shown in Figure 8.2. As a consequence, equations presented in Section 8.4.3 and Section 8.4.4 for GenCo are also different from similar equations developed in Section 8.3.3 and Section 8.3.4 for LSE. As discussed in Chapter 7, utility of a risk-free non-local bilateral trade and a risk-free local bilateral trade is calculated by equation (7.9) and equation (7.11) respectively.

8.4.3 Retained Strategic Reward

GenCo makes compromises in successive rounds, to make negotiations a success, by deciding how much of the total strategic reward must me retained in a particular round. Above described method of calculating total strategic reward in FABS is compared with another way [7] of estimating bilateral transaction reward. In [7] total assumed reward only depends on energy prices in strategic price set whereas, considering quantities used in equation (7.9) and equation (7.11), in FABS total strategic reward also depends on fuel consumption based coefficients of GenCo and optimal power quantity allocations to LSE at energy prices in the set. Therefore, total strategic reward, used in FABS, is a better measure of bilateral transaction reward as compared to total assumed reward used in [7].

If GenCo insists on an extreme stance of obtaining its total strategic reward then it offers *maximum strategic price* in each round. However, if LSE is not willing to accept *maximum strategic price* offered by GenCo then bilateral negotiation fails. On the other extreme, if GenCo relinquishes its total strategic reward then it offers *minimum strategic price* in each round. In such case, GenCo may succeed in bilateral negotiations but at the cost of losing its total strategic reward. In practice, bilateral negotiation typically involves a number of rounds of concessionary price offers by GenCo g and concessionary price bids by LSE l. GenCo g has a private limit on the maximum number of rounds for bilateral negotiation, T^g, and if it fails to reach a bilateral agreement by round T^g then it withdraws from negotiation. Since GenCo g does not have access to LSE l's private limit on the maximum number of rounds, it does not know the maximum number of rounds that can possibly take place between the two of them. Based on its own private limit, T^g, and current negotiation round, t, GenCo g perceives that remaining fraction of total negotiation time is $1-t/T^g$.

GenCo tries to secure a bilateral transaction by the end of its time limit while attempting to retain maximum possible strategic reward, in each round. GenCo retains a fraction of its total strategic reward that is directly proportional to its perception of remaining fraction of total negotiation time. GenCo calculates its retained strategic reward in round t, $Q^g_{l,retained}(t)$, as a fraction of the total strategic reward, $Q^g_{l,TOTAL}$, that is directly proportional to its perception of remaining negotiation time in round t, $1-t/T^g$, by,

$$Q^g_{l,retained}(t) = \left(1-t/T^g\right)Q^g_{l,TOTAL} \tag{8.7}$$

8.4.4 Strategic Price and Quantity Offer

A GenCo uses retained strategic reward value to select its price offer to an LSE in each round. A GenCo can find strategic price offer in round t, $sp^{g,offer}_l(t)$, corresponding to retained strategic reward in round t, $Q^g_{l,retained}(t)$, if it knows a general mathematical relationship between a price, sp^g_l, in strategic price set, S^g_l, and retained strategic reward at that price, $Q^g_{l,retained}\left(sp^g_l\right)$. By rewriting equation (8.6), relationship between a price sp^g_l and retained strategic reward at the price, $Q^g_{l,retained}\left(sp^g_l\right)$, is expressed as,

$$Q^g_{l,retained}\left(sp^g_l\right) = \sum_{\pi=sp^g_{l,\min}}^{sp^g_l}\left\{U^g_l(\pi)-U^g_l\left(sp^g_{l,\min}\right)\right\}\Delta\pi \tag{8.8}$$

Using equation (8.8), GenCo g calculates $Q^{g}_{l,retained}\left(sp^{g}_{l}\right)$ for each price sp^{g}_{l} in the strategic price set, S^{g}_{l}, and stores the calculated values in a table that is consulted in each negotiation round. In the table, GenCo g looks up the price sp^{g}_{l} at which stored value of retained strategic reward, $Q^{g}_{l,retained}\left(sp^{g}_{l}\right)$, equals or most closely approximates retained strategic reward for round t, $Q^{g}_{l,retained}\left(t\right)$, calculated from equation (8.3). Consequently, GenCo g selects the price sp^{g}_{l} as its strategic price offer to LSE l in round t, $sp^{g,offer}_{l}\left(t\right)$. After choosing the strategic price offer, $sp^{g,offer}_{l}\left(t\right)$, GenCo g looks up its power allocation results, like hypothesized results shown in Figure 8.3, and selects power quantity corresponding to the chosen price as its strategic quantity offer for bilateral transaction with LSE l in round t, $sq^{g,offer}_{l}\left(t\right)$.

Based on transaction protocol discussed in Section 8.2 and mathematical model presented in this section, a GenCo's negotiation algorithm for utility based strategy is shown in Section 8.4.5. The step by step algorithm conforms to the protocol and refers to equations developed during discussion of utility based strategy's mathematical model. Moreover, a summary of steps in the negotiation algorithm was provided at the beginning of Section 8.4.

8.4.5 Negotiation Algorithm

1) **For** each LSE l **Do**
   a) Evaluate total strategic reward $Q^{g}_{l,TOTAL}$ by (8.6) of bilateral transaction.
   b) Using equation (8.8), calculate $Q^{g}_{l,retained}\left(sp^{g}_{l}\right)$ for each price sp^{g}_{l} in the strategic price set S^{g}_{l} and store the calculated values in a look-up table
2) Set round to one ($t=1$)
3) **While** round <= maximum rounds ($t \le T^{g}$) **Do**
   a) **For** each LSE l **Do**
      i) Receive strategic price bid, $sp^{l,bid}_{g}\left(t\right)$, and strategic quantity bid, $sq^{l,bid}_{g}\left(t\right)$, for purchase of energy.

ii) Compute retained strategic reward $Q^{g}_{l,retained}(t)$ by (8.7).

iii) In the look-up table, find price sp^{g}_{l} at which stored value of retained strategic reward, $Q^{g}_{l,retained}\left(sp^{g}_{l}\right)$, equals retained strategic reward for round *t*, $Q^{g}_{l,retained}(t)$

iv) Choose sp^{g}_{l} as strategic price offer $sp^{g,offer}_{l}(t)$, for sale of energy.

v) Determine strategic quantity offer $sq^{g,offer}_{l}(t)$, corresponding to the strategic price offer $sp^{g,offer}_{l}(t)$, for sale of energy.

vi) **If** strategic price offer < strategic price bid $\left(sp^{g,offer}_{l}(t) < sp^{l,bid}_{g}(t)\right)$ **Then**

(1) agreed price = strategic price bid $\left(ap^{g}_{l} = sp^{l,bid}_{g}(t)\right)$ and agreed quantity = strategic quantity bid $\left(aq^{g}_{l} = sq^{l,bid}_{g}(t)\right)$

(2) Convey agreed price ap^{g}_{l} and agreed quantity aq^{g}_{l}, for sale of energy to LSE *l*.

vii) Else

(1) Convey strategic price offer $sp^{g,offer}_{l}(t)$ and strategic quantity offer $sq^{g,offer}_{l}(t)$, for sale of energy to LSE *l*.

b) Increment round by one ($t = t + 1$).

8.5 Utility and Bayesian Learning based Strategy of Generation Company

In each round, LSE agents submit price and quantity bids recommended by the trading utility based strategy, presented in Section 8.3. Similarly, GenCo's trading utility based strategy, presented in Section 8.4, suggests price and quantity offers for each round. However, depending on history of responses from a trading partner in successive negotiation rounds, Bayesian learning can discover private information of the trading partner in bilateral negotiation. In FABS, only GenCo agents are equipped with Bayesian learning capability to clearly demonstrate the advantage gained by a learning GenCo agent over a non-learning LSE agent. A GenCo agent builds on its utility based strategy to develop a new utility-and-learning based strategy. Hereafter, GenCo's utility based strategy, presented in Section 8.4, is referred as its old strategy and utility-and-learning based strategy, discussed in this Section, is referred as its new strategy.

A GenCo agent uses Bayesian learning method to estimate the maximum price that an LSE agent will be willing to bid in last round of bilateral negotiation. After updating its estimate of the LSE's private intention in a round GenCo anticipates that over the remaining rounds LSE will continue to increase its price bids up to the estimated value. According to the new strategy, GenCo opts for more controlled reduction of offer prices than proposed by the old strategy. GenCo hopes that the new strategy's controlled reduction of offer prices will culminate in sale of energy at a higher price than would have been possible with the old strategy. Further details of the controlled reduction of offer prices are covered in the rest of this Section.

Since a GenCo's new utility-and-learning based strategy builds on its old utility based strategy, mathematical models of the two strategies are similar. For both strategies, a GenCo agent calculates total strategic reward in exactly the same way as shown in Section 8.4.1. Furthermore, in either strategy, a GenCo agent finds its strategic price and quantity offers from the retained strategic reward as explained in Section 8.4.1. However, the strategies differ in calculation of a GenCo's retained strategic reward, as explained next. A GenCo's strategic price offer and resulting retained strategic reward have a direct relationship, i.e. both increase or decrease together, as confirmed by equation (8.8). Therefore, compared to the old strategy, the new strategy's controlled reduction of offer prices leads to a greater retained strategic reward.

Description of the new strategy's mathematical model is provided in subsections 8.5.1 to 8.5.4. A brief outline of contents covered in each of these subsections is provided here. The estimated price, serving as foundation of the new strategy, must be treated with caution because of estimation errors in Bayesian learning. If the price estimated by GenCo is assumed to have the same value as the actual price, privately selected by LSE, then it can lead to problems discussed in subsection 8.5.1.

Subsection 8.5.2 explains upper and lower bounds that apply to the estimated price in a practical bilateral negotiation scenario. Based on the estimated price, a price control ratio and a reward withholding factor are calculated as shown in subsection 8.5.3. According to the new strategy, GenCo's retained strategic reward has two components that are termed essential and premium rewards. The essential reward is calculated in the same as the old strategy's retained strategic reward. Conversely, the withholding factor determines premium component of retained strategic reward, as discussed in subsection 8.5.4.

GenCo's negotiation algorithm for the new utility-and-learning based strategy is presented in Section 8.5.5. An overview of steps in the negotiation algorithm is provided here. In step 1 of the algorithm, GenCo calculates and stores total strategic reward as well as retained strategic reward at each price in its strategic price set. GenCo needs the stored strategic reward results in all negotiation rounds. In step 2, GenCo sets current round to the first round of bilateral negotiation. Step 3 consists of GenCo's actions while negotiation rounds are in progress. GenCo carries out step 3-a for each LSE before moving to the next round in step 3-b. In steps 3-a-i and 3-a-ii GenCo receives bid from an LSE and calculates essential reward respectively. Since GenCo only needs premium reward in intermediate negotiation rounds, it only carries out step 3-a-iii in those rounds. In steps 3-a-iv to 3-a-vii, GenCo determines offer suggested by its own strategy for the LSE. In step 3-a-viii, GenCo compares the price offer suggested by its strategy with price bid received from the LSE. If the self-suggested price offer is less than the received price bid then GenCo accepts the bid. Otherwise, GenCo submits strategic price offer to the LSE, as shown in step 3-a-ix.

8.5.1 Problems with Assuming that an Estimated Price has Same Value as the Actual Price

Since estimation by Bayesian learning is prone to errors, a GenCo must not assume that GenCo *g*'s estimate of LSE *l*'s *maximum strategic price* in round *t*, $sp_{l,\max}^{g}(t)$ has same value as LSE *l*'s actual privately chosen *maximum strategic price* for GenCo *g*, $sp_{g,\max}^{l}$. In fact, the LSE's actual price, $sp_{g,\max}^{l}$, may be different from the estimated price, $sp_{l,\max}^{g}(t)$ and if GenCo assumes they are the same then it can face following problems.

It is possible that LSE's actual price, $sp_{g,\max}^{l}$, is higher than GenCo's estimated price, $sp_{l,\max}^{g}(t)$, but GenCo decreases its price offer down to $sp_{l,\max}^{g}(t)$. In this case, GenCo faces a low-price sale problem because it ends up selling its energy at a lower price than it would have obtained by cautiously using the estimated price, $sp_{l,\max}^{g}(t)$, for controlled reduction of offer prices. If LSE's actual price, $sp_{g,\max}^{l}$, is lower than GenCo's estimated price, $sp_{l,\max}^{g}(t)$ but GenCo assumes that the estimated price has the same vale as the actual price then GenCo decides to hold its price offer at $sp_{l,\max}^{g}(t)$. As explained in Chapter 3, *bilateral negotiations* between GenCos and LSEs are both *competitive* and *cooperative*. If a GenCo holds its offer price to an LSE then it shows fully *competitive* behaviour that lacks any *cooperative* gesture. In reaction, if the LSE invokes a behaviour dependent strategy and chooses to hold its bid price then bilateral negotiation will fail.

Note that successful negotiation is desired by both GenCo and LSE because each one benefits from utility of the bilateral transaction. If GenCo uses the estimated price as merely an indication and cautiously reduces offer prices in a controlled way then it can simultaneously minimize chances of low-price sale and negotiation failure.

8.5.2 Practical Upper and Lower Bounds of an Estimated Price

LSE's *maximum strategic price* is the maximum price that LSE is willing to bid to GenCo *g* in the last round, $sp_{g,\max}^{l}$. As already mentioned, GenCo's estimation of an LSE's maximum strategic price by Bayesian learning is prone to errors. If GenCo's estimated price, $sp_{l,\max}^{g}(t)$, is higher than its strategic price offer in the previous round, $sp_{l}^{g,offer}(t-1)$, then the estimate is reduced to $sp_{l}^{g,offer}(t-1)$ because LSE cannot submit a higher price bid than an already known price offer, $sp_{l}^{g,offer}(t-1)$.

On the other extreme, if GenCo's estimated price, $sp_{l,\max}^{g}(t)$, is lower than its *minimum strategic price*, $sp_{l,\min}^{g}$, then the estimate is raised to $sp_{l,\min}^{g}$ because GenCo cannot offer a lower price than $sp_{l,\min}^{g}$. As a result, GenCo restricts its estimated price, $sp_{l,\max}^{g}(t)$, to an upper bound equal to the previous offer, $sp_{l}^{g,offer}(t-1)$, and a lower bound equal to the *minimum strategic price*, $sp_{l,\min}^{g}$, i.e. $sp_{l}^{g,offer}(t-1) \geq sp_{l,\max}^{g}(t) \geq sp_{l,\min}^{g}$.

8.5.3 Price Control Ratio and Reward Withholding Factor

This section explains how a GenCo uses its bounded estimate of LSE's *maximum strategic price*, $sp_{l}^{g,offer}(t-1) \geq sp_{l,\max}^{g}(t) \geq sp_{l,\min}^{g}$, to calculate a price control ratio, $CR_{l}^{g}(t)$, that determines a reward withholding factor, $\omega_{l}^{g}(t)$. GenCo only calculates the withholding factor, $\omega_{l}^{g}(t)$ for an intermediate negotiation round *t*, $1 < t < T^{g}$, because of following reasons. In the first round, $t = 1$, GenCo cannot estimate LSE's *maximum strategic price* by Bayesian learning because that requires knowledge of LSE's price bids in at least two consecutive rounds. In consequence, GenCo is unable to determine its withholding factor for the first round. For the last round in its perception, $t = T^{g}$, GenCo is willing to lower its price offer to *minimum strategic price*, $sp_{l,\min}^{g}$, to avoid negotiation failure. GenCo does not use any withholding factor in the last round because, as a last resort, it aims to secure a bilateral transaction that was recommended by portfolio optimization due to its utility.

For an intermediate negotiation round *t*, $1 < t < T^{g}$, GenCo's calculation method for the price control ratio, $CR_{l}^{g}(t)$, is explained here. GenCo's price holding margin equals the difference between its estimate of LSE's *maximum strategic price*, $sp_{l,\max}^{g}(t)$ and *minimum strategic price*, $sp_{l,\min}^{g}$. GenCo's price reduction margin equals the difference between strategic price offer in the previous round, $sp_{l}^{g,offer}(t-1)$, and *minimum strategic price*, $sp_{l,\min}^{g}$. For controlled reduction of offer prices, GenCo divides the price holding margin by the price reduction margin to calculate a control ratio for round *t*, $CR_l^g\left(t\right)$, by,

$$CR_l^g\left(t\right)=\frac{price\ holding\ margin}{price\ reduction\ margin}=\frac{sp_{l,\max}^{g}\left(t\right)-sp_{l,\min}^{g}}{sp_l^{g,offer}\left(t-1\right)-sp_{l,\min}^{g}} \tag{8.9}$$

Although equation (8.9) is an original work of this thesis, its concept is derived from [14]. The control ratio is dependent on practical bounds of estimated price, $sp_l^{g,offer}\left(t-1\right)\geq sp_{l,\max}^{g}\left(t\right)\geq sp_{l,\min}^{g}$. In case of the upper bound, estimated price, $sp_{l,\max}^{g}\left(t\right)$, is same as previous offer, $sp_l^{g,offer}\left(t-1\right)$ and as a result control ratio for round *t*, $CR_l^g\left(t\right)$, has a value of 1. The unity value of control ratio intimates that GenCo should hold its offer its offer price but that action may lead to negotiation failure. On the other extreme, at lower bound, estimated price, $sp_{l,\max}^{g}\left(t\right)$, is same as minimum possible offer, $sp_{l,\min}^{g}$, and control ratio for round *t*, $CR_l^g\left(t\right)$, becomes 0. The zero value of control ratio indicates that GenCo must reduce its offer prices according to the utility based strategy and should not control the reduction any further. But that course of action may result in low-price sale problem for GenCo.

When determining a withholding factor based on the control ratio, GenCo wants to make sure that even in case of a Bayesian estimation error its withholding factor does not reach extremes of zero or one like the control ratio. GenCo avoids the both extremes, and the consequent problems, by limiting the withholding factor between 0.25 and 0.75 as,

$$\omega_l^g\left(t\right)=0.25+\frac{CR_l^g\left(t\right)}{2} \tag{8.10}$$

Calculation of withholding factor, $\omega_l^g\left(t\right)$, by equation (8.10) ensures that for any value of the control ratio, $CR_l^g\left(t\right)$, value of withholding factor, $\omega_l^g\left(t\right)$, remains between 0.25 and 0.75 inclusive, in an intermediate negotiation round *t*, $1<t<T^g$.

8.5.4 Essential and Premium Components of Retained Strategic Reward

For the new strategy, GenCo's retained strategic reward has two components that are termed essential and premium. In each round, GenCo's retained strategic reward by the old strategy is the essential reward that must be retained by the new strategy as well. Origin of the premium component of GenCo's retained strategic reward by the new strategy is described as follows. GenCo's retained strategic reward by the new strategy in the previous round is termed prior reward. Given that in each intermediate round GenCo holds the prior reward and has to safeguard the essential reward, GenCo pays attention to the difference between the two rewards. Based on the already determined withholding factor, GenCo's new strategy establishes that the fraction of the difference that is directly proportional to the withholding factor must be retained as the premium reward. Mathematical formulations for the retained strategic reward are explained in the following paragraphs of this subsection.

As shown in equation (8.7) for calculation of GenCo's retained strategic reward by the old strategy, GenCo's essential retained strategic reward by the new strategy, $Q_{l,retained}^{g,essential}(t)$, is given by,

$$Q_{l,retained}^{g,essential}(t) = \left(1 - t / T^{g}\right) Q_{l,TOTAL}^{g} \tag{8.11}$$

Substituting GenCo's strategic price offer for the previous round, $sp_{l}^{g,offer}(t-1)$, in equation (8.8), GenCo's prior retained strategic reward at the previously offered strategic price, $Q_{l,retained}^{g,prior}\left(sp_{l}^{g,offer}(t-1)\right)$, is given by ,

$$Q_{l,retained}^{g,prior}\left(sp_{l}^{g,offer}(t-1)\right) = \sum_{\pi = sp_{l,\min}^{g}}^{sp_{l}^{g,offer}(t-1)} \left\{U_{l}^{g}(\pi) - U_{l}^{g}\left(sp_{l,\min}^{g}\right)\right\}\Delta\pi \tag{8.12}$$

In each intermediate round *t*, using the essential reward, $Q_{l,retained}^{g,essential}(t)$, the prior reward, $Q_{l,retained}^{g,prior}\left(sp_{l}^{g,offer}(t-1)\right)$, and the withholding factor, $\omega_{l}^{g}(t)$, GenCo's new strategy calculates premium retained strategic reward, $Q_{l,retained}^{g,premium}(t)$, as,

$$Q_{l,retained}^{g,premium}\left(t\right)=\omega_l^g\left(t\right)\left\{Q_{l,retained}^{g,prior}\left(sp_l^{g,offer}\left(t-1\right)\right)-Q_{l,retained}^{g,essential}\left(t\right)\right\} \tag{8.13}$$

The new strategy's retained strategic reward of GenCo g for bilateral transaction with LSE l, $Q_{l,retained}^{g}\left(t\right)$, is calculated as,

$$Q_{l,retained}^{g}\left(t\right)=\begin{cases} Q_{l,retained}^{g,essential}\left(t\right) & , \quad t=1 \\ Q_{l,retained}^{g,essential}\left(t\right)+Q_{l,retained}^{g,premium}\left(t\right) & , \quad 1<t<T^g \\ Q_{l,retained}^{g,essential}\left(t\right) & , \quad t=T^g \end{cases} \tag{8.14}$$

Due to the premium component of retained strategic reward in intermediate rounds, the new strategy selects a higher price, i.e. more beneficial sale price for GenCo, than one suggested by the old strategy. A GenCo's retained strategic reward and corresponding strategic price offer have a direct relationship, as shown in equation (8.8). For either strategy, a GenCo agent finds its strategic price and quantity offers from the retained strategic reward as already explained in Section 8.4.1.

8.5.5 Negotiation Algorithm

1) **For** each LSE l **Do**
    a) Evaluate total strategic reward $Q_{l,TOTAL}^{g}$ by (8.6) of bilateral transaction.
    b) Using equation (8.8), calculate $Q_{l,retained}^{g}\left(sp_l^g\right)$ for each price sp_l^g in the strategic price set S_l^g and store the calculated values in a look-up table
2) Set round to one ($t=1$)
3) **While** round <= maximum rounds ($t\le T^g$) **Do**
    a) **For** each LSE l **Do**
        i) Receive strategic price bid, $sp_g^{l,bid}\left(t\right)$, and strategic quantity bid, $sq_g^{l,bid}\left(t\right)$, for purchase of energy.
        ii) Compute essential retained strategic reward $Q_{l,retained}^{g,essential}\left(t\right)$ by (8.11).
        iii) **If** it is an **Intermediate Rounds**, $1<t<T^g$, **Do**

(1) After subjecting the estimated price to upper and lower bounds, $sp_l^{g,offer}(t-1) \geq sp_{l,\max}^{g}(t) \geq sp_{l,\min}^{g}$, calculate control ratio, $CR_l^g(t)$ by equation (8.9).

(2) Compute withholding factor, $\omega_l^g(t)$, as shown in equation (8.10)

(3) In the look-up table, find GenCo's prior retained strategic reward at the previously offered strategic price, $Q_{l,retained}^{g,prior}\left(sp_l^{g,offer}(t-1)\right)$

(4) Using equation (8.13), find premium retained strategic reward $Q_{l,retained}^{g,premium}(t)$

iv) Compute retained strategic reward $Q_{l,retained}^{g}(t)$ by (8.14).

v) In the look-up table, find price sp_l^g at which stored value of retained strategic reward, $Q_{l,retained}^{g}\left(sp_l^g\right)$, equals retained strategic reward for round *t*, $Q_{l,retained}^{g}(t)$

vi) Choose sp_l^g as strategic price offer $sp_l^{g,offer}(t)$, for sale of energy.

vii) Determine strategic quantity offer $sq_l^{g,offer}(t)$, corresponding to the strategic price offer $sp_l^{g,offer}(t)$, for sale of energy.

viii) **If** strategic price offer < strategic price bid $\left(sp_l^{g,offer}(t) < sp_g^{l,bid}(t)\right)$

Then

(1) agreed price = strategic price bid $\left(ap_l^g = sp_g^{l,bid}(t)\right)$ and agreed quantity = strategic quantity bid $\left(aq_l^g = sq_g^{l,bid}(t)\right)$

(2) Convey agreed price ap_l^g and agreed quantity aq_l^g, for sale of energy to LSE *l*.

ix) Else

(1) Convey strategic price offer $sp_l^{g,offer}(t)$ and strategic quantity offer $sq_l^{g,offer}(t)$, for sale of energy to LSE *l*.

b) Increment round by one ($t = t+1$).

8.6 Case Studies

This Chapter has two case studies that are termed productive bilateral negotiation and enhanced bilateral negotiation, as explained next. In case both negotiating partners use their utility based strategies, bilateral negotiations succeed in securing bilateral transactions – hence the case study is named productive bilateral negotiation. By comparison, in case of enhanced bilateral negotiation, GenCo's utility based strategy is supported by Bayesian learning but LSE only uses its utility base strategy. The two case studies are designed to demonstrate that: (i) the utility based strategies of both negotiating partners are capable of securing bilateral transactions and (ii) GenCo can succeed in securing a more favourable bilateral transaction if its utility based strategy is enhanced by Bayesian learning but LSE has no learning capability. Although the developed negotiation strategies are generic, this thesis has only tested the negotiation strategies on the five node test grid. As future work, performance of the negotiation strategies needs to be evaluated for larger test grids containing more generators and loads.

8.7 Results

Difference in results of the Productive and Enhanced Bilateral Negotiations between GenCo-1 and LSE-1 are illustrated in Figure 8.5. The Productive Bilateral Negotiation between GenCo-1 and LSE-1 proceeds as follows. LSE-1 initiates each round and bids energy prices \$20/MWh, \$22.5/MWh and \$25.7/MWh in rounds 1, 2 and 3 respectively. In response, GenCo-1 offers energy prices \$41.2/MWh, \$38.1/MWh and \$34.4/MWh in rounds 1, 2 and 3 respectively. Furthermore, since both are interested in trading 19.60MW at any price in their negotiable price set, they offer/bid for 19.60MW power quantity in all rounds. Note that both want to bilaterally trade 19.60MW of power in every hour of the coming year that has 360 days in FABS. The bilateral negotiation succeeds in round 4 because LSE-1 bids for 19.60MW at \$30.4/MWh and GenCo-1 accepts the quantity and price. Consequently, \$5,148,057 becomes payable by LSE-1 to GenCo-1 against the bilateral transaction.

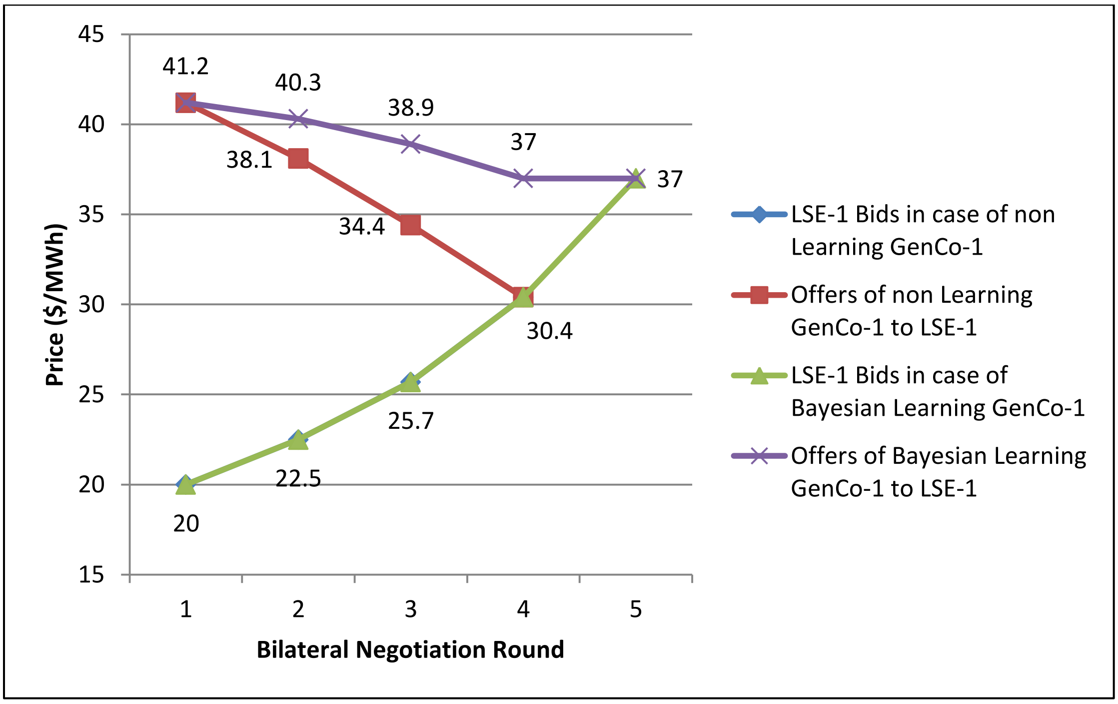

Figure 8.5 Results of Productive bilateral negotiations and enhanced bilateral negotiations between GenCo-1 and LSE-1

Bayesian learning enables a GenCo to estimate the maximum price that an LSE agent will be willing to bid in last round of bilateral negotiation. Consequently, GenCo reduces its offers prices to the LSE in a restrained way. The Enhanced Bilateral Negotiation between GenCo-1 and LSE-1 ensues as follows. Since LSE-1 is using utility based strategy as in case of the Productive Bilateral Negotiation, it still bids energy prices $20/MWh, $22.5/MWh, $25.7/MWh and $30.4/MWh in rounds 1, 2, 3 and 4 respectively. As in case of Productive Bilateral Negotiation, GenCo-1 offers $41.2/MWh in round 1 because it needs at least two interactions with LSE-1 to start its Bayesian learning. However, due to Bayesian learning in rounds 2, 3 and 4, GenCo-1 reduces its offer prices in a restrained way as shown in Figure 8.5. Instead of offering $38.1/MWh, $34.4/MWh and $30.4/MWh, GenCo-1 offers $40.3/MWh, $38.9/MWh and $37.0/MWh in rounds 2, 3 and 4 respectively. The bilateral negotiation succeeds in round 5 when LSE-1 accepts GenCo-1's round 4 offer of 19.60MW at $37.0/MWh. In consequence, $6,265,728 becomes payable by LSE-1 to GenCo-1 against the bilateral transaction. Compared to the Productive Bilateral

Negotiation, GenCo-1 earns $1,117,671 more from bilateral transaction with LSE-1 by the Enhanced Bilateral Negotiation.

Difference in results of the Productive and Enhanced Bilateral Negotiations between GenCo-4 and LSE-3 are illustrated in Figure 8.6. The Productive Bilateral Negotiation between GenCo-4 and LSE-3 progresses as follows. LSE-3 initiates each round and bids for 75MW power quantity at energy prices $67.2/MWh, $68.7/MWh, $70.5/MWh and $72.9/MWh in rounds 1, 2, 3 and 4 respectively. In response GenCo-4 offers 128MW power quantity at energy prices $89.2/MWh, $86.1/MWh, $82.4/MWh and $77.6/MWh in rounds 1, 2, 3 and 4 respectively. In round 5, LSE-3 agrees to GenCo-4's price offer of $77.6/MWh in round 4. However, since LSE-3 only wants to buy 75MW from GenCo-4, it only accepts 75MW out of GenCo-4's offered quantity of 128MW in round 4. GenCo-4 agrees to the reduction in quantity and the bilateral negotiation succeeds for 75MW at $77.6/MWh. As a result of the bilateral transaction, $50,284,800 becomes payable by LSE-3 to GenCo-4 for bilateral trade of 75MW in every hour of the coming simulation year of 360 days.

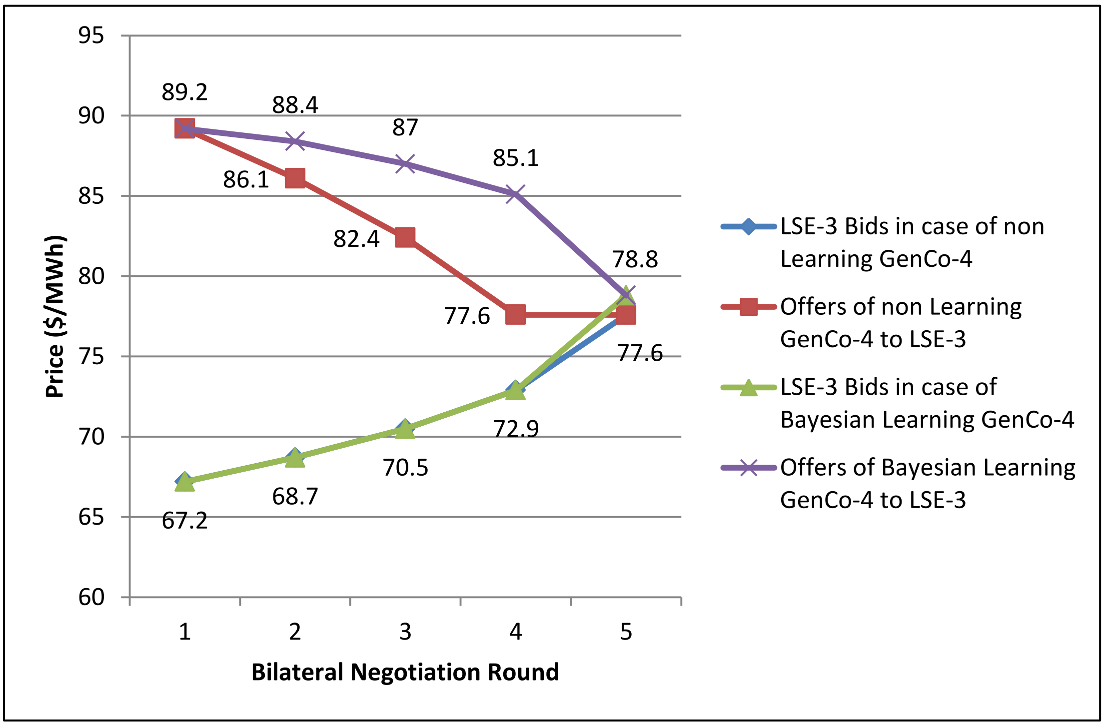

Figure 8.6 Results of Productive bilateral negotiations and enhanced bilateral negotiations between GenCo-4 and LSE-3

The Enhanced Bilateral Negotiation between GenCo-4 and LSE-3 advances as follows. Since LSE-3 is using utility based strategy as in case of the Productive Bilateral Negotiation, it still bids energy prices \$67.2/MWh, \$68.7/MWh, \$70.5/MWh and \$72.9/MWh in rounds 1, 2, 3 and 4 respectively. As in case of Productive Bilateral Negotiation, GenCo-4 offers \$89.2/MWh in round 1 because it needs at least two interactions with LSE-3 to start its Bayesian learning. However, due to Bayesian learning in rounds 2, 3 and 4, GenCo-4 reduces its offer prices in a restrained way as shown in Figure 8.5. Instead of offering \$86.1/MWh, \$82.4/MWh and \$77.6/MWh, GenCo-4 offers \$8.4/MWh, \$87/MWh and \$85.1/MWh in rounds 2, 3 and 4 respectively. In round 5, LSE-3 agrees to GenCo-4's price offer of \$78.8/MWh in round 4. Despite the agreement on price, LSE-3 only accepts 75MW quantity out of 128MW offered by GenCo-4. In response, GenCo-4 agrees to the reduction in quantity and the bilateral negotiation succeeds for 75MW at \$78.8/MWh. As a result of the bilateral transaction, \$51,062,400 becomes payable by LSE-3 to GenCo-4. Compared to the Productive Bilateral Negotiation, GenCo-4 earns \$777,600 more from bilateral transaction with LSE-3 by the Enhanced Bilateral Negotiation.

8.8 Conclusions

Based on trading utility results of match making over a specified price set, this Chapter introduces a new way of measuring reward of a bilateral transaction option, instead of assuming the reward like [7]. Moreover, since a market participant is unsure about private intentions of others, it has to rely on a perception of remaining negotiation time. A main negotiation strategy, termed utility based strategy, is developed by combining the trading reward and the perception of remaining negotiation time for both GenCo and LSE. Furthermore, each GenCo is enabled to estimate the ultimate price of its opponent by Bayesian learning, followed by a new method to adapt its main utility based strategy in response to opponent behaviour. The new bilateral negotiation strategies for both GenCo and LSE are integrated in FABS.

Utility based negotiation strategies are productive for securing bilateral transactions between market participants. Bayesian learning enables a market participant to update estimates of negotiating partners' ultimate prices during negotiation. A new method is presented in this Chapter to use the estimated prices and proceed with bilateral negotiations in a restrained manner. A Bayesian learning market participant gains advantage over a non-learning market participant and secures a more favourable bilateral transaction.

8.9 References

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9 Conclusions and Future Work

This Chapter concludes the overall thesis and presents some ideas for future work.

9.1 Conclusions

This thesis aimed to provide publicly available modelling of decision making for direct-search bilateral transactions in deregulated wholesale electricity markets. This thesis set the following main objectives.

- First main thesis objective was to design annual planning methods for match making in direct-search bilateral transactions between Generation Companies and Load Serving Entities.
- The second main thesis objective was to develop new computational methods to establish optimal dynamic strategies for bilateral negotiations between the market participants.
- The third main thesis objective involved a novel learning based adaptation method to adjust dynamic strategies of Generation Companies during bilateral negotiations.

As secondary objectives, the thesis aspired to optimize Financial Transmission Rights bids and achieve combined simulation of financial transmission instruments, bilateral transactions and day-ahead auction in a single agent-based computational framework. All main and secondary objectives of thesis have been achieved.

This thesis has achieved simulation of match making for direct-search bilateral transactions, without assuming that bilateral transactions are organized, transmission constraints do not exist, participants have complete information about others or match making is a random process. Moreover, it has demonstrated that simulation of bilateral negotiations can utilize heuristics, accommodate dynamic prices of organized electricity markets and avoid estimation errors in learning.

This thesis presents agent-based modelling of decentralized bilateral transactions in electricity markets. The thesis also reports combined agent-based simulation of annual Financial Transmission Rights auction and annual Auction Revenue Rights allocation along with annual bilateral transactions and organized day-ahead market for energy. Previous agent-based simulation platforms for wholesale electricity markets existed as proprietary software or used simplified models. In case of proprietary software, mathematical modelling details of bilateral transactions were not available in public domain. For simplified models, some assumptions were not representative of real world bilateral transactions. In this thesis, detailed mathematical modelling of bilateral transactions is provided to facilitate accurate and in-depth understanding of implemented model.

This research has made following contributions to existing knowledge pool. Improvements in portfolio optimization procedures of Generation Companies and Load Serving Entities have led to development of systematic match making algorithms. The new optimization procedures and algorithms accommodate upper limits on bilateral transactions and available Financial Transmission Rights. A novel application of bilateral transactions' utilities has developed dynamic bilateral strategies for Generation Companies and Load Serving Entities. Moreover, dynamic strategy of a Generation Company is supported by new adaptive strategy for bilateral negotiations.

9.2 Future Work

Research work presented in this thesis can be extended in a number of ways. Some ideas for extending the research are as follows. Agent-based electricity market modelling and simulation tool developed for this thesis is currently being tested for anticipated release as open-source software in future. The open-source and agent-based approach will ensure that additional market mechanisms can be incorporated by the software users to meet their specific research or training needs. Due to the combined simulation capability, it is anticipated that the platform will be useful in exploring mutual effects of individual market mechanisms and overall dynamics of deregulated wholesale electricity markets.

Monthly Financial Transmission Rights can be added to the simulation. Monthly short-duration bilateral transactions by broker or electronic bulletin-board can be included in the simulation. If DC Optimal Power Flow solution is infeasible for requested Financial Bilateral Transactions then ISO agent can be allowed to reduce the bilateral transactions to achieve a feasible solution. Unforeseen transmission failure and transmission security constraints can be introduced in optimal power flow and Simultaneous Feasibility Test of independent system operator. Market participant agents can be equipped with decision making for long-duration physical bilateral transactions.

Appendix A - Test Grid Data

Test grid shown in Figure A.1 and originally proposed in [1], has been used in this thesis. Data of the smaller test grid is adopted from [2] and built in both AMES and FABS software. Capacities of transmission lines and characteristics of GenCos are listed in Table A.1 and Table A.2 respectively. Daily load profiles for fixed (price-inelastic) demand are illustrated in Figure A.2. The load profiles show that peak loads at each node occur in hour 17 in the test grid. Base load of each LSE is chosen to be slightly below minimum points on the load profiles corresponding to hour 4. Peak and base loads of LSEs are listed in Table A.3.

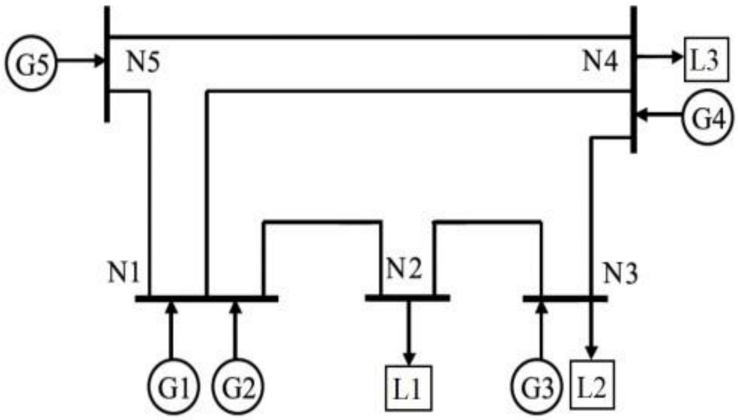

Figure A.1 One-Line Diagram of Test Grid

Table A.1 Transmission Line Capacities

Source Location	**Sink Location**	**Transmission Line Capacities (MW)**
Node-1	Node-2	250
Node-1	Node-4	150
Node-1	Node-5	400
Node-2	Node-3	350
Node-3	Node-4	240
Node-4	Node-5	240

Table A.2 Capacities of Generators

Generation Company	**Capacity (MW)**	**a_g (\$/MW^{2}h)**	**b_g (\$/MWh)**	**c_g (\$/h)**
GenCo-1	110.0	0.005	14.0	0.0
GenCo-2	100.0	0.006	15.0	0.0
GenCo-3	520.0	0.010	25.0	0.0
GenCo-4	200.0	0.012	30.0	0.0
GenCo-5	600.0	0.007	10.0	0.0

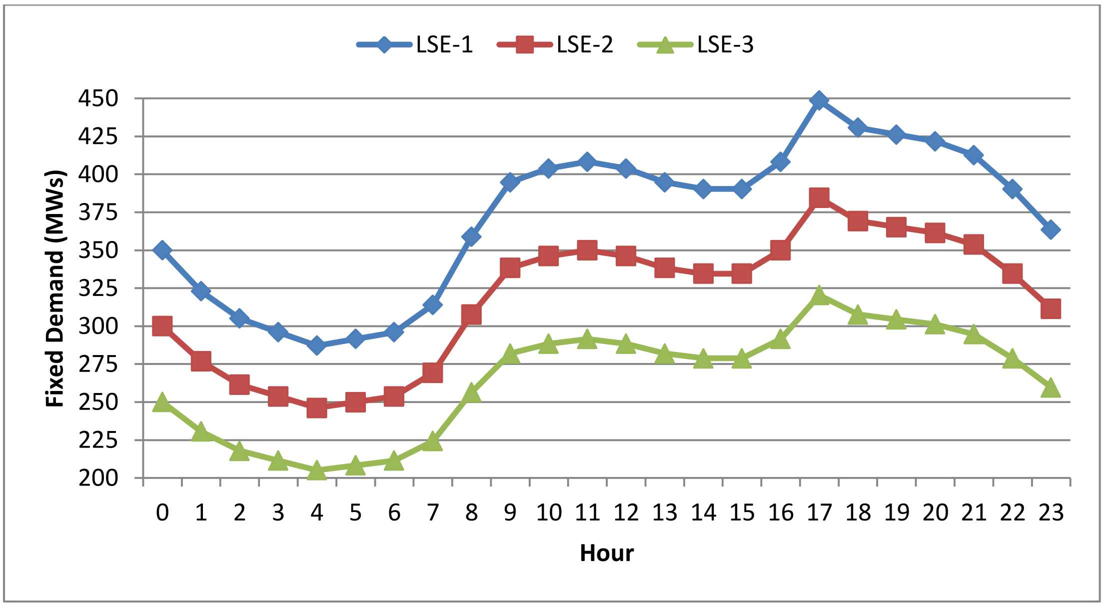

Figure A.2 LSE Hourly Fixed Demands

Table A.3 Peak Load and Base Load Data of LSEs

LSE	Peak Load (MW)	Base Load (MW)
LSE-1	448.62	272.80
LSE-2	384.53	233.82
LSE-3	320.44	194.85

Input data of historical LMPs for FABS was obtained from AMES as explained here. AMES was first run with all existing settings but modified simulation stopping rules to ensure that day-ahead energy market continuously runs for one simulation year (12 months of 30 days each). This simulation of day-ahead energy market in AMES gave output of one year's LMP data for the test grid. Consequently the LMP data was used as input in FABS to calculate overall expectations, variances, covariances and standard deviations of LMPs at all nodes, irrespective of trading intervals. The overall expectations, variances and standard deviations of LMPs at all nodes are shown in Table A.4, whereas the covariances of LMPs are listed in Table A.5

Although sometimes an investor can be risk neutral (A=0), or even a risk lover (A<0), practical decision makers are normally risk averse (A>0). After stressing that there is no authoritative data to describe risk preference of electricity market participants and based on a set of principles, [3] determines that A can lie in range of 2.89 and 6.1. According to [4], risk aversion factors of investors generally range between 2.0 and 4.0. Following from [4], A=3.0 is considered an average risk aversion factor and consequently A>3.0 is assumed a high risk aversion factor in this thesis. In this thesis, if overall variance of LMP at market participant's local node is greater than 1000 then it chooses a high risk aversion factor of 4.0. Otherwise, a market participant uses average risk aversion factor of 3.0. Table A.4 also shows risk aversion factors used by market participants at all nodes.

Table A.4 Results of Statistical Analysis of Historic Prices

Node	**Overall Expectation of LMPs ($/MWh)**	**Overall Variance of LMPs**	**Overall Standard Deviation of LMPs ($/MWh)**	**Risk Aversion Factor**
Node-1	31.0	211.9	14.7	3.0
Node-2	196.3	5119.4	82.2	4.0
Node-3	165.0	3333.9	66.3	4.0
Node-4	78.9	486.6	24.5	3.0
Node-5	39.5	192.5	13.9	3.0

Table A.5 Results of Covariance of Historic Prices

	Node-1	Node-2	Node-3	Node-4	Node-5
Node-1	214.854	-188.512	-112.089	98.076	194.151
Node-2	-188.512	6763.784	5446.573	1824.242	168.320
Node-3	-112.089	5446.573	4393.406	1497.196	173.214
Node-4	98.076	1824.242	1497.196	597.817	186.672
Node-5	194.151	168.320	173.214	186.672	192.825

Power transfer distribution factors were calculated by using AMES. This was achieved by removing all generators and loads from the system and only adding 1MW generation unit at desired source node and 1MW load demand at desired sink node. The resulting power flows in transmission lines were noted as power transfer distribution factors. The distribution factors calculated by this method in column two of Table A.6, for transmission line between nodes 1 and 4 (Node-1-Node-4), were verified by comparison with those in [1].

Following optimization problems are solved in FABS: (i) FTR bid optimization by each LSE; (ii) FTR auction optimization by ISO; (iii) portfolio optimization by every GenCo and LSE. Each optimization problem is solved by a specific Matlab optimization tool that has been named in Chapter that discussed solution of respective optimization problem. Moreover, input data and output data of each optimization problem is also discussed in its respective Chapter. However, for all of the above-mentioned optimization problems, input data is sent from Java environment of FABS to Matlab and output data is retrieved back in FABS.

Table A.6 Power Transfer Distribution Factors

Power Flow From Source to Sink		Transmission line between Origin Node (upper row) and End Node (lower row)					
Source Node	Sink Node	Node-1	Node-1	Node-1	Node-2	Node-3	Node-4
		Node-2	Node-4	Node-5	Node-3	Node-4	Node-5
Node-1	**Node-2**	0.67	0.18	0.15	-0.33	-0.33	-0.15
Node-1	**Node-3**	0.54	0.25	0.21	0.54	-0.46	-0.21
Node-1	**Node-4**	0.19	0.44	0.37	0.19	0.19	-0.37
Node-3	**Node-2**	0.13	-0.07	-0.06	-0.87	0.13	0.06
Node-3	**Node-3**	0.0	0.0	0.0	0.0	0.0	0.0
Node-3	**Node-4**	-0.35	0.19	0.16	-0.35	0.65	-0.16
Node-4	**Node-2**	0.48	-0.26	-0.22	-0.52	-0.52	0.22
Node-4	**Node-3**	0.35	-0.19	-0.16	0.35	-0.65	0.16
Node-4	**Node-4**	0.0	0.0	0.0	0.0	0.0	0.0
Node-5	**Node-2**	0.64	0.10	-0.74	-0.36	-0.36	0.26
Node-5	**Node-3**	0.51	0.17	-0.68	0.51	-0.49	-0.32
Node-5	**Node-4**	0.16	0.36	-0.52	0.16	0.16	-0.48

References

[1] "Business Practice Manual for Financial Transmission Rights," Revision 1 ed: ISO New England, USA, 2003.

[2] J. Sun and L. Tesfatsion, "Dynamic Testing of Wholesale Power Market Designs: An Open-Source Agent-Based Framework," *Computational Economics*, vol. 30, pp. 291-327, 2007.

[3] F. Donghan, G. Deqiang, Z. Jin, and N. Yixin, "Supplier Asset Allocation in a Pool-Based Electricity Market," *Power Systems, IEEE Transactions on,* vol. 22, pp. 1129-1138, 2007.

[4] M. Liu and F. F. Wu, "Portfolio optimization in electricity markets," *Electric Power Systems Research,* vol. 77, pp. 1000-1009, 2006.

Appendix B - Estimation of Maximum Strategic Price by Bayesian Learning

Bayesian learning is a statistical learning method that is based on Bayes' rule. As discussed in literature review in Chapter 3, Bayesian learning has been used for estimating ultimate price of negotiating partner in reviewed research papers. In FABS, each LSE determines its own maximum strategic price, $sp^{l}_{g,\max}$, as explained in Chapter 8. Exact value of an LSE's maximum strategic price is private information. However, GenCo g uses Bayesian learning method [1] to get an estimated maximum strategic price of LSE l in round t, $\overset{g}{sp}_{l,\max}(t)$, where $t > 1$. The Bayesian learning method [1], presented in this Appendix, was programmed in Java language and incorporated in FABS for this thesis.

A *negotiable price set* between GenCo g and LSE l was defined in Chapter 7. Knowing the *minimum negotiable price*, $np^{g}_{l,\min}$, and the *maximum negotiable price*, $np^{g}_{l,\max}$, GenCo g's valid *hypothesis set* for maximum strategic price of LSE l, H^{g}_{l}, is expressed as,

$$H^{g}_{l} = \left\{ np^{g}_{l,\min} + k : k = 0,1,\ldots, np^{g}_{l,\max} - np^{g}_{l,\min} \right\} \tag{B.1}$$

The *hypothesis set* contains H hypotheses where $H = 1 + np^{g}_{l,\max} - np^{g}_{l,\min}$ and hth hypothesis for LSE l is denoted as $\overset{g}{sp}_{l,h}$. It is assumed that initially the H hypotheses follow a uniform probability distribution. A uniform probability distribution means that initially each hypothesis is assumed to be equally likely. In this case, prior probability of each hypothesis is calculated as $1/H$.

The Bayesian learning method uses strategic price responses from LSE to get an updated estimate of LSE's maximum strategic price in each round, after the first round ($t > 1$). This price estimation requires a series of computations in a certain sequence presented in Section C.1 and discussed as follows. In the second round ($t=2$) of negotiation, strategic price bid received by GenCo from LSE *l* in the first round, $sp_g^{l,bid}(1)$, and GenCo's strategic price offer to LSE *l* in the first round, $sp_l^{g,offer}(1)$, are used to calculate $\alpha_l^g(t-1)=\alpha_l^g(1)$ by (B.2). This initialization of α_l^g, for LSE *l*, is only required in the second round ($t=2$) of negotiation. In each round after the second round, $\alpha_l^g(t-1)$ is always available from computation in the previous round. Bayesian learning method uses the history of strategic price bid responses from LSE to calculate $\alpha_l^g(t)$ by using (B.3).

$$\alpha_l^g(1)=\left|1-sp_g^{l,bid}(1)/sp_l^{g,offer}(1)\right| \tag{B.2}$$

$$\alpha_l^g(t)=\left|1-sp_g^{l,bid}(t)\times\frac{\left(1-\alpha_l^g(t-1)\right)}{sp_g^{l,bid}(t-1)}\right| \tag{B.3}$$

According to agreed bilateral transaction protocol, although an LSE can hold on to its strategic price, it cannot decrease it in subsequent rounds. This makes it possible to eliminate some of the hypotheses in view of the latest strategic price of LSE *l*. If *h*th hypothesis $sp_{l,h}^{g}$ is greater than or equal to strategic price bid of LSE *l* $sp_g^{l,bid}(t)$, then $sp_{l,h}^{g}$ remains valid. Otherwise $sp_{l,h}^{g}$ becomes invalid because due to already agreed bilateral transaction protocol, it is no longer possible for LSE *l* to propose a lower strategic price bid in the next round, $sp_g^{l,bid}(t+1)\not< sp_g^{l,bid}(t)$. If *h*th hypothesis $sp_{l,h}^{g}$ has become invalid then its prior probability is set to zero, $Pr^{t-1}\left(sp_{l,h}^{g}\right)=0$.

For each hypothesis of each LSE *l*, $\mu_{l,h}^g(t)$ can be calculated by using (B.4). Calculation of $\mu_{l,h}^g(t)$ by GenCo, is based on an assumption that $sp_g^{l,bid}(t)$ of LSE *l* will gradually move closer to LSE's $sp_{g,\max}^{l}$ over successive negotiation rounds. Calculated values of $\mu_{l,h}^g(t)$ are used in (B.5) for determining values of conditional probability $Pr^t\left(sp_g^{l,bid}(t)\,|\,sp_{l,h}^{g}\right)$. It is assumed that conditional probability of *h*th valid hypothesis, $sp_{l,h}^{g}$, follows a normal distribution $N\left(\mu_{l,h}^{g}(t),1\right)$.

$$\mu_{l,h}^{g}(t) = sp_{l,h}^{g} \times \left(1-\alpha_l^g(t)\right) \tag{B.4}$$

$$Pr^t\left(sp_g^{l,bid}(t)\,|\,sp_{l,h}^{g}\right) = \frac{\frac{1}{\sqrt{2\pi}}e^{-\frac{\left(sp_g^{l,bid}(t)-\mu_{l,h}^{g}(t)\right)^2}{2}}}{\sum_{h=1}^{H}\frac{1}{\sqrt{2\pi}}e^{-\frac{\left(sp_g^{l,bid}(t)-\mu_{l,h}^{g}(t)\right)^2}{2}}} \tag{B.5}$$

If $sp_{l,h}^{g} \geq sp_g^{l,bid}(t)$ then $sp_{l,h}^{g}$ is valid and Bayes rule is used in (B.6) to update belief about LSE's maximum strategic price by determining posterior probability of each valid hypothesis, $Pr^t\left(sp_{l,h}^{g}\,|\,sp_g^{l,bid}(t)\right)$. Otherwise $sp_{l,h}^{g}$ is invalid and its posterior probability does not need to be calculated by (B.6) because the probability is zero, $Pr^t\left(sp_{l,h}^{g}\,|\,sp_g^{l,bid}(t)\right)=0$. At this stage, posterior probability in current round *t*, $Pr^t\left(sp_{l,h}^{g}\,|\,sp_g^{l,bid}(t)\right)$, is assigned as updated prior probability for round *t*, $Pr^t\left(sp_{l,h}^{g}\right)$, by (B.7). In the coming round, the updated prior probability is referred as $Pr^{t-1}\left(sp_{l,h}^{g}\right)$ and used for calculations in (B.6).

$$Pr^t\left(sp_{l,h}^{g}\,|\,sp_g^{l,bid}(t)\right) = \frac{Pr^{t-1}\left(sp_{l,h}^{g}\right)\times Pr^t\left(sp_g^{l,bid}(t)\,|\,sp_{l,h}^{g}\right)}{\sum_{h=1}^{H}Pr^{t-1}\left(sp_{l,h}^{g}\right)\times Pr^t\left(sp_g^{l,bid}(t)\,|\,sp_{l,h}^{g}\right)} \tag{B.6}$$

$$Pr^t\left(sp_{l,h}^{g}\right) = Pr^t\left(sp_{l,h}^{g}\,|\,sp_g^{l,bid}(t)\right) \tag{B.7}$$

Finally, updated belief about valid hypotheses is used to determine estimated maximum strategic price of an LSE in current round *t*, $sp_{l,\max}^{g}(t)$, by (B.8).

$$sp_{l,\max}^{g}(t) = \sum_{h=\min}^{\max} sp_{l,h}^{g} \times Pr^{t}\left(sp_{l,h}^{g} \mid sp_{g}^{l,bid}(t)\right) \tag{B.8}$$

A step-by-step Bayesian learning Method is presented as follows.

1) **For** each LSE l in every intermediate round ($1 < t < T^{g}$) **Do**

a) **If** second round ($t = 2$) **Then**

i) Determine H hypotheses of LSE's maximum strategic price.

ii) Initialize prior probability, $Pr^{t}\left(sp_{l,h}^{g}\right) = Pr^{0}\left(sp_{l,h}^{g}\right)$, for all H hypotheses.

iii) Compute $\alpha_{l}^{g}(1)$ by using (B.2).

b) Compute $\alpha_{l}^{g}(t)$ by using (B.3).

c) **For** each valid hypothesis of maximum strategic price **Do**

i) Invalidate *h*th hypothesis, $sp_{l,h}^{g}$, if it is impossible, by setting its prior probability to zero, $Pr^{t-1}\left(sp_{l,h}^{g}\right) = 0$.

ii) Compute $\mu_{l,h}^{g}(t)$ by using (B.4).

iii) Compute conditional probability $Pr^{t}\left(dp_{l}^{g}(t) \mid sp_{l,h}^{g}\right)$ by using (B.5).

iv) Update posterior probability $Pr^{t}\left(sp_{l,h}^{g} \mid dp_{l}^{g}(t)\right)$ by using (B.6).

v) Update prior probability $Pr^{t}\left(sp_{l,h}^{g}\right)$ by (B.7) for next round.

d) Estimate maximum strategic price of LSE, $sp_{l,\max}^{g}(t)$, by using (B.8).

References

[1] S. Kwang Mong, G. Yuanyuan, and S. Benyun, "BLGAN: Bayesian Learning and Genetic Algorithm for Supporting Negotiation With Incomplete Information," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on,* vol. 39, pp. 198-211, 2009.

Appendix C - Daily Day-Ahead Market and Monthly Financial Settlements

In FABS, after simulation of decentralized bilateral negotiations for annual bilateral transactions, day-ahead market commences. All market participants may not secure sufficient bilateral transactions to fully meet their energy trading requirements. Therefore, ISO operates the day-ahead market and participants get another opportunity to fulfil their remaining energy trading requirements. Day-ahead market and market settlement models of java based AMES software were extended for FABS to include Financial Bilateral Transactions (FBTs) as well as Financial Transmission Rights (FTRs) and Auction Revenue Rights (ARRs). Therefore, all mathematical formulation and market processes related to FBTs, FTRs or ARRs, in this Appendix, are contributions of this thesis. Moreover, if any formulation or market process of AMES is used without any extension in FABS then it is clearly mentioned in this Appendix.

GenCos and LSEs submit their energy trading requirements to ISO as discussed in Section C.1. ISO determines optimal energy trading conditions for all market participants for each hour as described in Section C.2. Monthly market settlements for financial transmission instruments and energy are determined as discussed in Section 0. Overall results of electricity market, consisting of financial transmission instruments, Financial Bilateral Transactions and day-ahead market are presented in Section C.4.

C.1 Submissions of GenCos and LSEs for Day-ahead Market

The day-ahead market includes a day-ahead auction for energy and Financial Bilateral Transactions. Financial bilateral transactions are not considered a part of the day-ahead auction because their prices are not determined by clearing prices of the auction. However, Financial Bilateral Transactions are a part of the day-ahead market because transmission congestion charges are payable according to hourly LMPs of the day-ahead market. For the day-ahead auction, GenCos and LSEs submit hourly price-sensitive energy offers and demand bids to ISO respectively. LSEs also submit hourly price-inelastic load demands to ISO for the day-ahead auction. GenCos and LSEs submit power quantities of agreed Financial Bilateral Transactions to ISO for the day-ahead market.

Submissions of GenCos

GenCo g's actual cost parameters corresponding to price-sensitive supply:

$$a_g^{Sa} = a_g \tag{C.1}$$

$$b_g^{Sa} = 2 \cdot a_g \cdot p_g^{FBT} + b_g \tag{C.2}$$

GenCo g's generation limits corresponding to price-sensitive supply:

$$Gn_g^{S,\max} = p_g^{\max} - p_g^{FBT} \tag{C.3}$$

$$Gn_g^{S,\min} = 0 \tag{C.4}$$

Each GenCo uses reinforcement learning, described in [1], to improve its supply offers for next day. The reinforcement learning process in AMES is used without any modification in FABS. After reinforcement learning, GenCo g's reported cost parameters corresponding to price-sensitive supply are denoted by a_g^{Sr}, b_g^{Sr}.

GenCo g's hourly reported price-sensitive supply offer to ISO for day-ahead auction consists of a_g^{Sr}, b_g^{Sr}, $Gn_g^{S,\min}$ and $Gn_g^{S,\max}$. In addition, GenCo g sends quantities of Financial Bilateral Transactions (FBT) with all LSEs and their sum p_g^{FBT} to ISO for the day-ahead market.

Submissions of LSEs

LSE l's hourly price-sensitive demand bid to ISO for day-ahead auction consists of c_l^S, d_l^S, $Ld_l^{S,\min}$ and $Ld_l^{S,\max}$. LSE l also reports hourly price-inelastic demand p_l^I to ISO for day-ahead auction. In addition, LSE l sends quantities of Financial Bilateral Transactions (FBT) with all GenCos and their sum p_l^{FBT} to ISO for the day-ahead market.

C.2 DC Optimal Power Flow Formulation for Day-ahead Market

This section presents mathematical model of DC-OPF algorithm of AMES [2], that is used for this thesis. ISO uses all submissions of GenCos and LSEs and determines a DC Optimal Power Flow (DC-OPF) solution for each hour of the next day. In addition to calculating LMPs and line power flows, DC-OPF solution determines optimal generation schedules for GenCos and price-sensitive loads of LSEs. ISO publicly announces results of day-ahead auction for GenCos and LSEs.

For each hour, ISO prepares for DC-OPF by determining total net surplus and cost using equations (C.5) to (C.12).

GenCo g's reported cost function corresponding to price-sensitive supply:

$$Cost_g^{Sr}\left(p_g^S\right) = a_g^{Sr} \cdot \left(p_g^S\right)^2 + b_g^{Sr} \cdot p_g^S \tag{C.5}$$

The gross surplus of LSE l corresponding to its price-sensitive demand bid:

$$Surplus_l^S\left(p_l^S\right) = c_l^S \cdot p_l^S - d_l^S \cdot \left(p_l^S\right)^2 \tag{C.6}$$

Total net surplus corresponding to price-sensitive demand bids and reported price-sensitive supply offers:

$$TNS^S\left(p_G^S, p_L^S\right) = Surplus^S\left(p_L^S\right) - Cost^{Sr}\left(p_G^S\right) \quad \text{(C.7)}$$

where

$$p_G^S = \left(p_{g=1}^S, p_{g=2}^S, \cdots, p_{g=G}^S\right) \quad \text{(C.8)}$$

$$p_L^S = \left(p_{l=1}^S, p_{l=2}^S, \cdots, p_{l=L}^S\right) \quad \text{(C.9)}$$

$$Surplus^S\left(p_L^S\right) = \sum_{l=1}^{L} Surplus_l^S\left(p_l^S\right) \quad \text{(C.10)}$$

$$Cost^{Sr}\left(p_G^S\right) = \sum_{g=1}^{G} Cost_g^{Sr}\left(p_g^S\right) \quad \text{(C.11)}$$

Total net cost function corresponding to price-sensitive demand bids and reported price-sensitive supply offers:

$$TNC^S\left(p_G^S, p_L^S\right) = -TNS^S\left(p_G^S, p_L^S\right) \quad \text{(C.12)}$$

For a commonly used representation of DC-OPF problem with price-sensitive demand bids and supply offers, solution objective is to minimize total net costs corresponding to the price-sensitive supply and demand, $TNC^S\left(p_G^S, p_L^S\right)$, subject to various constraints.

DC Optimal Power Flow Problem

Minimize

$$TNC^S\left(p_G^S, p_L^S\right) \quad \text{(C.13)}$$

with respect to

real power price-sensitive generation, real power price-sensitive loads, and voltage angles

$$p_g^S, g = 1, \cdots, G; p_l^S, l = 1, \cdots, L; \delta_n, n = 1, \cdots, N \tag{C.14}$$

subject to

(i) Real power balance constraint for each node n = 1, ..., N: [5]

$$\sum_{g \in G_n} \left(p_g^S + p_g^{FBT} \right) - \sum_{l \in L_n} \left(p_l^S + p_l^I + p_l^{FBT} \right) - \sum_{oe \in TL \| oe \in TL} Fl_{oe} = 0 \tag{C.15}$$

alternatively

$$\sum_{g \in G_n} p_g^S - \sum_{l \in L_n} p_l^S - \sum_{oe \in TL \| oe \in TL} Fl_{oe} = \sum_{l \in L_n} \left(p_l^I + p_l^{FBT} \right) - \sum_{g \in G_n} p_g^{FBT} \tag{C.16}$$

where

$$Fl_{oe} = \left[V_o^{\ 2} \right] B_{oe} \left(\delta_o - \delta_e \right) \tag{C.17}$$

(ii) Real power thermal constraint for each transmission line $oe \in TL$:

$$\left| Fl_{oe} \right| \leq Fl_{oe}^{capacity} \tag{C.18}$$

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[5] For this thesis, real power injections and withdrawals for Financial Bilateral Transactions (FBTs) at each node are incorporated in the real power balance constraints in DC-OPF of AMES, as shown in equations (C.15) and (C.16).

(iii) Real power price-sensitive operating capacity constraints for each GenCo g = 1, .., G:

$$Gn_g^{S,\min} \le p_g^S \le Gn_g^{S,\max} \tag{C.19}$$

(iv) Real power price-sensitive load constraints for each LSE l = 1, .., L:

$$Ld_l^{S,\min} \le p_l^S \le Ld_l^{S,\max} \tag{C.20}$$

(v) Voltage angle setting at reference Node-1:

$$\delta_1 = 0 \tag{C.21}$$

Following information in quotation marks regarding the DC-OPF problem (C.13) -(C.21) is adopted from [3]. "The DC-OPF problem (C.13)-(C.21) can be solved as a strictly convex quadratic programming problem either by using the nodal balance constraints (C.15) to substitute out for voltage angles [4] or by using an augmented Lagrangian method [5] in which the objective function (C.13) is augmented with a quadratic penalty term for the sum of squared voltage-angle differences, as shown and explained later, to produce a strictly convex objective function with respect to all of the choice variables (C.14)." The former substitution method for voltage angle elimination prevents direct determination of solution values for LMPs because LMPs are the shadow prices for the nodal balance constraints (C.15). The latter augmented Lagrangian approach is taken by developers of AMES because it permits direct determination of optimal LMPs and voltage angle solutions. Therefore, augmented objective function in AMES includes a quadratic penalty term for the sum of squared voltage-angle differences, $\sum_{oe \in TL} \left(\delta_o - \delta_e\right)^2$, adjusted by penalty weight π, as shown in (C.22),

$$TNC^S\left(p_G^S, p_L^S\right) + \pi \sum_{oe \in TL} \left(\delta_o - \delta_e\right)^2 \tag{C.22}$$

Apart from permitting direct determination of optimal LMPs and voltage angle solutions, the augmentation "provides a way to conduct sensitivity experiments on the size of the voltage angle differences that could be informative for estimating the size and pattern of AC-DC approximation errors" [2]. It is critical to note that the DC-OPF problem (C.13)-(C.21) is considered a valid approximation of underlying AC-OPF problem subject to a simplifying assumption, among others, that voltage angle difference across transmission lines remain small. Since this thesis has not developed the augmented DC-OPF objective function of AMES, further details of the augmentation are beyond the scope of this thesis but can be seen in [2].

C.3 Monthly Market Settlements

In FABS, each simulation month consists of 30 days. Payments for energy and financial transmission instruments (FTRs and ARRs) take place on monthly basis. ISO conducts annual ARR allocation and FTR auction at the beginning of simulation in FABS. Formulae based on guidelines in [6], are provided in this subsection for monthly financial settlements of ARRs and FTRs respectively.

ARR Settlements

ISO determines its total annual FTR auction revenue by (C.23).

$$FTR_{ISO}^{revenue} = \sum_{sk} FTR_{sk}^{cleared,quantity} \times FTR_{sk}^{cleared,price} \tag{C.23}$$

Clearing prices of the FTR auction determine tentative financial value of the ARRs. Thus ISO calculates total anticipated payable to LSEs due to annual ARR allocations by (C.24).

$$ARR_{ISO}^{payable} = \sum_{sk} ARR_{sk}^{awarded,quantity} \times FTR_{sk}^{cleared,price} \tag{C.24}$$

Since ISO is a non-profit organization, it must ensure revenue neutrality in ARR pay-outs. ISO uses (C.25) to calculate a revenue neutrality adjustment factor.

$$RNAF_{ISO} = FTR_{ISO}^{revenue} \Big/ ARR_{ISO}^{payable} \tag{C.25}$$

ISO defers ARR payments until the end of month and uses (C.26) to calculate auction revenue credit for LSE at sink *k*.

$$ARC_k = \sum_{s=1}^{S} RNAF_{ISO} \times ARR_{sk}^{awarded,quantity} \times FTR_{sk}^{cleared,price} \tag{C.26}$$

FTR Settlements

FTRs are tentatively valued according to difference in LMPs at source and sink nodes. So ISO calculates a target allocation (TA) against each FTR between *s* and *k* for each hour *h by* (C.27).

$$TA_{sk}^{h} = FTR_{sk}^{cleared,quantity} \times \left(\lambda_{k,h} - \lambda_{s,h}\right) \tag{C.27}$$

Since obligation type FTRs are simulated, loads may be eligible for credits or may be liable to payments depending on the difference in LMP between the source and the sink. If TA_{sk}^{h} is positive then it is added to monthly positive target allocation of LSE at *k*, TA_k^{+}. Otherwise TA_{sk}^{h} is added to monthly transmission congestion revenue (TCR) of ISO from FTRs, TCR_{ISO}^{FTR}. This process is repeated for all hours of a day and for all days in a month.

ISO also determines its overall monthly transmission congestion revenue from DAM, TCR_{ISO}^{DAM}. This is calculated by subtracting total payments to GenCos from total income from LSEs over whole month. Then ISO calculates total monthly transmission congestion revenue (C.28).

$$TCR_{ISO}^{total} = TCR_{ISO}^{FTR} + TCR_{ISO}^{DAM} \tag{C.28}$$

ISO also determines total positive target allocations, TA_{total}^{+}, for all sink nodes *k* (C.29).

$$TA_{total}^{+} = \sum_{k=1}^{K} TA_k^{+} \tag{C.29}$$

ISO announces LMPs of day-ahead market on daily basis but FTR settlements are deferred until the end of each month. ISO has to ensure revenue neutrality in paying transmission congestion credits (TCCs) to loads for holding FTRs.

If $TA_{total}^{+} \leq TCR_{ISO}^{total}$ then (C.30) is used to assign TCCs to LSE at node *k*.

$$TCC_k = TA_k^{+} \tag{C.30}$$

However, if $TA_{total}^{+} > TCR_{ISO}^{total}$ then (C.31) determines TCCs for LSE at node *k*.

$$TCC_k = \frac{TA_k^{+}}{TA_{total}^{+}} \times TCR_{ISO}^{total} \tag{C.31}$$

C.4 Hourly Cost and Revenues of GenCos and LSEs

Hourly costs and revenues of GenCos and LSEs are calculated by formulae in this subsection. To get monthly values, the hourly costs and revenues of a market participant are added for each hour of a day and for each day of a month. The difference in monthly revenue and cost of a GenCo determines its monthly profit. However, monthly credits due to ARRs and FTRs are also added to the difference in monthly revenue and cost of an LSE to calculate its monthly profit.

Hourly Costs of GenCos

GenCo g's actual cost function corresponding to price-sensitive supply:

$$Cost_g^{Sa}\left(p_g^S\right) = a_g^{Sa} \cdot p_g^S + b_g^{Sa} \cdot \left(p_g^S\right)^2 \tag{C.32}$$

GenCo g's actual cost function corresponding to supply for Financial Bilateral Transactions (FBT):

$$Cost_g^{FBT}\left(p_g^{FBT}\right) = a_g \cdot p_g^{FBT} + b_g \cdot \left(p_g^{FBT}\right)^2 \tag{C.33}$$

GenCo g's total hourly cost corresponding to all supplies:

$$Cost_g^{Total} = Cost_g^{Sa}\left(p_g^S\right) + Cost_g^{FBT}\left(p_g^{FBT}\right) \tag{C.34}$$

Hourly Revenues of GenCos

GenCo g's revenue function corresponding to price-sensitive supply:

$$Revenue_g^S\left(\lambda_g, p_g^S\right) = \lambda_g \cdot p_g^S \tag{C.35}$$

GenCo g's revenue from supply for Financial Bilateral Transactions (FBT):

$$Revenue_g^{FBT} = \sum_{l=1}^{L} ap_l^g \cdot a\rho_l^g \tag{C.36}$$

GenCo g's total hourly revenue from all supplies:

$$Revenue_g^{Total} = Revenue_g^S\left(\lambda_g, p_g^S\right) + Revenue_g^{FBT} \tag{C.37}$$

Hourly Costs of LSEs

LSE l's cost function corresponding to price-sensitive load:

$$Cost_l^S\left(\lambda_l, p_l^S\right) = \lambda_l \cdot p_l^S \tag{C.38}$$

LSE l's cost function corresponding to price-inelastic load:

$$Cost_l^I\left(\lambda_l, p_l^I\right) = \lambda_l \cdot p_l^I \tag{C.39}$$

LSE l's cost for load corresponding to Financial Bilateral Transactions (FBT):

$$Cost_l^{FBT} = \sum_{g=1}^{G} ap_g^l \cdot a\rho_g^l + \sum_{g=1}^{G} a\rho_g^l \cdot \left(\lambda_l - \lambda_g\right) \tag{C.40}$$

LSE l's total hourly cost for all loads:

$$Cost_l^{Total} = Cost_l^S\left(\lambda_l, p_l^S\right) + Cost_l^I\left(\lambda_l, p_l^I\right) + Cost_l^{FBT} \tag{C.41}$$

Hourly Revenues of LSEs

LSE *l*'s revenue function corresponding to price-sensitive load:

$$Revnue_l^S\left(\lambda_l, p_l^S\right) = \lambda_l \cdot p_l^S \tag{C.42}$$

LSE *l*'s revenue function corresponding to price-inelastic load:

$$Revnue_l^I\left(\gamma_{ln}, p_l^I\right) = \gamma_{ln} \cdot p_l^I \tag{C.43}$$

LSE *l*'s revenue corresponding to Financial Bilateral Transactions (FBT):

$$Revnue_l^{FBT} = \gamma_{ln} \cdot p_l^{FBT} \tag{C.44}$$

LSE *l*'s total hourly revenue corresponding to all loads:

$$Revnue_l^{Total} = Revnue_l^S\left(\lambda_l, p_l^S\right) + Revnue_l^I\left(\lambda_l, p_l^I\right) + Revnue_l^{FBT} \tag{C.45}$$

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[5] M. Shahidehpour, H. Yamin, and Z. Li, "Market Overview in Electric Power Systems," in *Market Operations in Electric Power Systems,* ed: John Wiley & Sons, Inc., 2002, pp. 1-20.

[6] "Business Practice Manual for Financial Transmission Rights," Revision 10 ed: ISO New England, USA, 2012.

Glossary

ARR – See Auction Revenue Right

Auction Revenue Right - A financial instrument that can hedge the cost of acquiring the Financial Transmission Right. Abbreviated ARR.

bid-based economic loads – Most competitive *price-sensitive load demands* of Load Serving Entities, determined and allowed by independent system operator.

bilateral negotiation – A terminal phase in decision making for bilateral transactions. If successful, it determines agreed amount and price for energy.

bilateral transaction – A contract for transfer of energy or financial responsibility for energy between a buyer and a seller.

competitive – A fully competitive task of electricity market participants.

complete information – A simulated market environment which assumes market participants and/or the market operator interact among themselves with complete information about others. Compare with incomplete information.

contract for difference – A financial instrument for hedging against congestion risk in North Pool. Abbreviated CfD. Compare with contract-for-difference.

contract-for-difference – A bilaterally agreed contract to settle difference if market design does not allow out of market settlement for energy. Can be combined with a self-schedule to achieve an implicit Financial Bilateral Transaction. Compare with contract for difference.

cooperative – A fully cooperative task of electricity market participants.

day-ahead auction – ISO collects GenCos' *price-sensitive supply offers* and LSEs' *price-sensitive demand bids* as well as *price-inelastic load demands* to conduct a day-ahead auction for determination of *offer-based economic schedules* and *bid-based economic loads*. Compare with day-ahead market.

day-ahead market – A day-ahead market organized by ISO for energy trading between market participants. It includes a day-ahead auction for determination of economic schedules. It can also include self-schedules, physical schedules and financial schedules by market participants. Compare with day-ahead auction.

dynamic – A market environment where prices or other conditions vary over time.

Compare with stationary.

dynamic strategy – An agent has a dynamic strategy if it adopts its behaviour after interaction with the environment. Compare with stationary strategy.

Financial Bilateral Transaction – A contract for transfer of financial responsibility for energy (not the physical flow of energy) between a buyer and a seller, to be fulfilled by a financial schedule.

financial schedule – An option to participate in day-ahead market to transfer the financial responsibility for energy (not the physical flow of energy) between a buyer and a seller, to fulfil a Financial Bilateral Transaction.

financial transmission instruments – A collective term for Financial Transmission Rights (FTR) and Auction Revenue Rights (ARR) from market participants' perspective. A collective term for Financial Transmission Rights (FTR) auction and Auction Revenue Rights (ARR) allocation from ISO's perspective.

Financial Transmission Right - A financial instrument that can hedge transmission congestion cost of a market participant. Abbreviated FTR.

FTR – See Financial Transmission Right

GenCo – See Generation Company

Generation Company – A Generation Company that produces and sells bulk-energy in any wholesale electricity market. Abbreviated GenCo.

incomplete information – A market environment where participants are unaware of private risk preferences, bids data, actual costs or profits etc. of other participants. Compare with complete information.

independent system operator – A non-profit organization which is responsible for managing both transmission network and electricity market in the wholesale electricity markets of USA.

ISO – See independent system operator

LMP – See Locational Marginal Price

Load Serving Entity – A Load Serving Entity that buys bulk-energy from wholesale electricity market to serve retail loads. Abbreviated LSE.

Locational Marginal Price – Total cost of meeting an additional unit of energy requirement at a particular location on transmission network, including costs of congestion and losses in transmission network. Abbreviated LMP.

LSE – See Load Serving Entity

market operator – A private organization which organizes energy auction in the wholesale electricity markets of EU.

market participants – GenCos as bulk-energy sellers and LSEs as bulk-energy buyers.

match making – An initial phase in decision making for bilateral transactions which determines suitable negotiation partners

mixed – A task of electricity market participants that has both competitive and cooperative characteristics.

negotiable price ranges – Price ranges in which a market participant explores suitability of its trading partners during match making

offer-based economic schedules – Most competitive *price-sensitive supply offers* of Generation Companies, determined and allowed by independent system operator.

physical bilateral transaction – A contract for transfer of energy (by the physical flow of energy) between a buyer and a seller, to be fulfilled by a *physical schedule*.

physical schedule – An option to participate in day-ahead market to transfer the energy (by the physical flow of energy) between a buyer and a seller, to fulfil a *physical bilateral transaction*.

power exchange – See market operator.

price-inelastic load demands – Load demands of Load Serving Entities that must be fulfilled, irrespective of market prices, by independent system operator.

price-sensitive load demands – submitted by LSEs and processed by ISO to determine which ones are most competitive (highest priced) and should be allowed as bid-based economic loads. These represent willingness of LSEs to buy specified energy quantities if LSEs can get energy prices that are lower or equal to their specified energy prices.

price-sensitive supply offers – submitted by GenCos and processed by ISO to determine which ones are most competitive (lowest priced) and should be allowed as offer-based economic schedules. These represent willingness of GenCos to sell specified energy quantities if GenCos can get energy prices that are higher or equal to their specified energy prices.

self-schedule – An option to participate in day-ahead market which allows generator to run at least at the self-schedule level and get paid at market price determined by ISO.

stationary – A simulated market environment which assumes fixed market conditions. Compare with dynamic.

stationary strategy –An agent has a stationary strategy if it shows deterministic behaviour that does not change after repeated interactions with the environment. Compare with dynamic strategy.

strategic price ranges – Price ranges in which a market participant intends to negotiate with its matched trading partners

systematic – The property of match making phase if it involves some non-random planning effort.

transmission congestion – A condition when energy flow through a transmission line reaches its maximum limit.

transmission congestion cost – A payment for congestion over transmission network.

transmission constraints – Maximum energy flow capability of transmission lines due to their physical limitations

transmission losses – Energy lost in transmission network because some energy is inevitably wasted as heat while flowing through transmission lines

transmission operator – A public body which manages transmission network in the wholesale electricity markets of EU.

virtual demand bids – energy demand bids by speculators who do not own any physical load demand

virtual supply offers – energy supply offers by speculators who do not own any physical power generation capacity