Minimisation of Energy Costs Considering Electric Vehicle for a Smart Home System

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Declaration

I hereby declare that this thesis is the results of the author's original research which is composed by the author himself. It has not been previously submitted for any examination led to the award of a degree.

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Abstract

Smart residential home systems have good potential for more efficient use of energy, reduced cost and less effects to environment. In order to adapt to new technologies such as electric vehicles (EVs), photovoltaic (PV) system, photovoltaic-thermal (PV-T) system, and solar water heater (SWH) system, novel demand side management (DSM) methods are required to effectively control EV and renewable technologies for residential energy systems. More importantly, customers play a key role in DSM as they have the energy usage choices according to their preferences. To understand the benefits for residential EV end users, their usage behaviours, such as driving behaviour, charging and discharging periods, willingness to participate to vehicle to grid (V2G), need to be considered in the DSM.

In this thesis work, a novel DSM model framework is developed for a residential home system, considering EV, energy storage system (ESS), renewable technologies, and human behaviours. Survey data are collected and analysed to support the model development. Based on model, minimisation of the energy costs of residential home systems is explored by controlling the charging/discharging status of EV and a separate ESS under practical constraints. Key factors such as the degradation cost of EV and ESS batteries, user's driving behaviour, and different types of electricity tariffs are included in the optimisation. Extensive case studies have been undertaken to investigate the operation strategies under various scenarios. The options and potential benefits of V2G are discussed.

To further investigate the DSM for residential homes with the use of renewable energy, two solar water heating systems, the hybrid PV-T and the PV-SWH, are considered into the energy cost evaluation. Models for both PV-T and PV-SWH are formulated and added into the modelling framework for residential home systems. Built on the work of optimal charging/discharging of EV and ESS, the optimal switch operations of the PV-SWH system have been calculated, through which further cost reduction can be achieved. For the option of PV-SWH with limited solar panel space, the split of areas between PV and SWH is determined through a pseudo-optimisation route.

Numerical studies have been conducted to examine the economic benefits of solar thermal collectors, the comparisons between PV-T and PV-SWH, and the effective use of the limited solar panel area for PV-SWH.

Finally, different appraisal methods are applied to analyse the investment worth of the residential energy household systems with optimal DSM. The most beneficial investment solutions are obtained from the relevant case studies.

Through the above systematic investigation of DSM for smart home energy systems, improved understanding on how to reduce energy cost for end users are obtained, including new insights on the benefits and conditions of V2G for EV users. The established modelling framework can easily include sub energy systems, e.g. EV, ESS, and renewable energy systems. Complex variation factors such as EV driving behaviour, external environment temperature, solar radiation, electricity tariffs are considered to achieve optimal operation strategies to reduce energy cost at residential home level. Financial analysis is applied to analyse the investment worth of these residential energy household systems. The optimal system choices for the end user are discussed through case studies.

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Acronyms

DOD	depth of discharge
DPB	discounted payback period
DSM	demand side management
ESS	energy storage system
CFL	compact fluorescent lamp
EV	electric vehicle
FIT	feed-in tariff
HAN	home area networks
NPV	net present value
OPF	operating cash flow
PB	payback period
PV	photovoltaic
SOC	state of charge
SWH	solar water heater
TOU	time-of-use
TVM	time value of money
WAN	wide area networks
V2G	vehicle-to-grid

Nomenclature

C_0, C_0^{EV}, C_0^{ESS}	battery purchase price, battery purchase prices for EV and ESS, £
C_{total}	total operational cost, £
$C_{purchase}$	cost to purchase electricity from the grid, £
C_{income}	income from selling electricity to the grid, £
C_{EV}	degradation cost of EV battery, £
C_{ESS}	degradation cost of the ESS battery, £
C_{SOC}	hourly cost of SOC related degradation, £
CF_{max}	maximum capacity fade constant (%)
C_{DOD}	DOD degradation cost, £
C_{SOC}^{EV}	SOC related degradation cost of EV, £
C_{DOD}^{EV}	DOD related degradation cost of EV, £
C_{SOC}^{ESS}	SOC related degradation cost of ESS, £
C_{DOD}^{ESS}	DOD related degradation cost of ESS, £
$d(l)$	the $l-th$ possible driving distance, km
d_{total}	maximum distance the EV can run with a fully charged battery, km
$d_{\exp}$	expected driving distance over the next driving period, km
α, β	model parameters for calculation of C_{SOC}
n_1	battery discharging cycles

ΔL_{DOD}	DOD of a particular discharging cycle
N_{total}	total number of discharging cycles corresponding to ΔL_{DOD}
N_d	total number of drives
P_1	output power of the PV system, kW
P_2	EV charging or discharging power, kW
P_3	input/output power of ESS, kW
P_4	load of the residential home, kW
P_5	input or output power from the grid, kW
p_{FIT}	feed-in tariff price, £/kWh
p_{k1}	probability of EV to park and plug in at home
p_{k2}	probability of EV driving on road
p_{k3}	probability of EV parking outside
p_l	probability of driving over the distance of $d(l)$
Q, Q_{EV}, Q_{ESS}	Battery, EV and ESS battery capacities, kWh
SOC_{IN}	initial value of state of charge
SOC_{EV}	EV state of charge
SOC_{LB}^{EV}	lower bound of the terminal SOC
$SOC_{EV-display}$	displayed SOC in the vehicle's panel
$SOC_{ESS-display}$	displayed SOC in ESS
τ	the average discharging efficiency of EV and ESS when power flows back to the grid
μ	electricity price, £/kWh

υ	feed-in tariff price, £/kWh
M	mass of storage capacity, kg
C_p	specific heat of water, 4187J/kg℃
P_u	collected solar power delivered to the storage tank, kW
P_l	power removed from storage tank to load, kW
P_e	auxiliary electricity heat power, kW
A_C	solar collect area, m^2
S	absorbed radiation, W
F_R	heat removal factor
U_L	product of the overall heat loss coefficient
T_s	storage tank hot water's temperature , ℃
T_a	temperature of the environment , ℃
I	solar irradiance, W
$\tau\alpha$	transmittance absorbance product
$\dot{m}$	mass flow rate, kg/s
T_{mu}	make-up water temperature, ℃
UA	storage tank loss coefficient
κ	storage tank back-up heat power
Z	permissible error range of the temperature, ℃
$T_{expected}$	expected hot water's temperature , ℃
c	ratio of the heat added to (or removed from) an object to reach the expected temperature change
E	energy change, J

ΔT	temperature change , ℃
C_I	initial investment, £
FV	future value of money, £
PV	present value of money, £
r	interest rate
n	number of compounding periods per year
t	number of years
DCI	discounted cash inflow, £
dr	discounted rate
χ	period to which the cash inflow relates
ω	cash inflow value factor
OPF_t	operating cash flow during the time period *t*
C_s	annual cost savings, £
C_m	annual maintenance fees of the smart home system, £
$C_{non-opt}$	annual cost without optimisation, £
C_{opt}	annual cost obtained by the optimised solution, £
C_e	annual electricity cost without optimisation, £
$C_{driving}$	traditional annual fuel consumption cost, £
ic_{pv}	installation costs of PV, £
ic_{ess}	installation costs of ESS, £
$ic_{charging}$	installation cost of EV home charging system, £
$ic_{control}$	installation cost of smart home control system, £

P_{load}	hourly electricity consumption, kW

Chapter 1 Introduction

1.1 Background

Electric vehicles (EVs) can contribute to deeply reduce greenhouse gas emission if the charging load of EV supplied from renewable energy resources [1]. In recent research development, minimisation of EV charging cost including vehicle-to-grid (V2G) has been widely investigated while considering battery degradation [2-4]. It can help to alleviate the peak demands of power and minimise the energy cost of users. With V2G, an EV can be used as an energy storage device that is able to inject the stored electric power back to the grid. This can be applied as a new type of energy source and utilised together with energy storage system (ESS) to achieve optimal operation of power systems [5]. In addition, the EV customers' driving usage such as driving time, parking time, and daily driving distance, which would certainly influence the charging and discharging of EVs and the cost [6]. In order to understand the benefits for residential EV end users, novel demand side management (DSM) method is required to effectively control EV and renewable technologies for residential energy systems; therefore, the mathematical optimisation method can be applied to find out the 'best' values of operating variables. The objective of the method aims to minimise the energy cost for residential energy system by controlling EV charging and renewable generation on/off status considering V2G and customer driving behaviours, such as driving behaviour, charging and discharging periods, willingness to participate to V2G.

1.2 Motivation and scope

In order to significantly reduce greenhouse gas emission and tackle the increasing carbon emission problem, electric vehicles (EVs) have become popular in the past decade, and the charging load of EVs supplied from renewable energy resources can help to alleviate transport emission [7, 8]. A reduction of 47%~78% greenhouse gas emissions can be achieved through the photovoltaic (PV)-powered EV technology, and the feed-in tariff (FIT) of PV power and the investment interest rate can be used in policy making tools to develop low carbon transportation systems [9]. In comparison to traditional combustion vehicles, PV-powered EVs have nearly 100% pollutant reduction potential for CO_2, SO_2 and NO [10].

In order to adapt to renewable generation technology, the traditional grids need to be evolved to smart grid. Smart grid is an electricity network that can intelligently interact with all of the users connected to it [11, 12] . It can help to manage the variability of renewable resources, enable consumers actively get involved, and allow more actions of consumption be responded back to the grid operator through smart metering systems. In the future, more and more end users will contribute to energy management in smart grid systems. This requires demand side management (DSM) activities that would improve utilisation of renewable resources to supply power to the end users. More importantly, customers play a major role in DSM as they have the choice from a range of products according to their preferences [13, 14]; therefore, analysis of DSM for smart residential homes becomes crucial in saving energy cost. To support systematic DSM under various scenarios, a mathematical modelling framework needs to be established for residential home energy systems, based on which DSM optimisation strategies can be explored.

As EVs become popular for energy management at the demand side, minimising the charging cost of EV is prerequisite to attract more end users to participate in the DSM schemes or other policies, therefore, optimal charging control of EVs, which aims to reduce cost of users, should be investigated. In addition, with the development of vehicle to grid (V2G) technology, an EV can be used as an energy storage device that is capable of injecting the stored electric power back to the grid. EVs can be applied as a new type of energy source and utilised together with the energy storage system (ESS) to achieve more cost reductions [15]. It is therefore important to include EV and ESS into the smart home energy system model .

Though V2G techniques provide wider options for control and optimisation of EV systems, V2G operation increases the cost of battery degradation, which needs to be considered in its applications [16]. Another issue is whether the EV owners would be willing to participate in a V2G program. The economic viability of V2G, primarily affected by the high cost of discharging to the grid, is a big issue for EV owners. This is often related to factors such as battery degradation, expensive battery pack and low FIT. It is discussed in [17] that a V2G service can lead to a reduced life-cycle of an EV. The power aggregators should operate either on pay-as-you-go basis or provide consumers with advanced cash payment in order to attract more EV owners participating in V2G. The promised rate of return for V2G may not be sufficient to attract widespread V2G participation due to the cost in grid connection, purchase of electricity and battery degradation [18]. The EV's battery pack will need to be replaced more frequently with V2G operation [19]. The battery aging cost induced by V2G may exceed the benefit brought from V2G, and substantial subsidies are required to trigger V2G service [20]. Therefore, it is important for residential home owners to consider whether V2G is economically beneficial in reducing their overall energy cost.

EV driving behaviours affect implementation of DSM programmes [21]. When EV is considered into the cost minimisation model of end users, the information of vehicle usage, such as driving time, parking time, and daily driving distance, will be important factors that influence the charging and discharging of EVs and the cost accordingly [21]. The EV usage factor has been ignored in most research. In this thesis, the EV usage probabilities will be included in the mathematical model. Quantities such as probabilities of EV parking and plugging in at home, probability of EV parking outside, probability that the EV is under driving and the probability of each driving, etc. will be obtained through survey data.

The use of renewable energy is a recent trend for smart residential homes. For a residential household energy management system, PV is not the only way to utilize the solar energy for the cost and energy reduction. Another technology that can help end users to reduce daily energy consumption is solar water heater (SWH). Comparing to PV which supplies power directly to the home, the electric back-up element of SWH can be controlled to supply sufficient amount of hot water as required. In this thesis, combination of PV and SWH will be considered in the residential home energy use optimisation system.

To support DSM at residential homes, initial investments are required for purchasing equipment for PV, SWH and ESS, which are usually not cheap for family users. Whether the cost savings calculated from the optimal operation can compensate the initial investments could be an issue. In this thesis, financial analysis will be performed using appropriate appraisal methods to assess and analyse the overall cost savings under the optimisation scheme when initial investment is considered.

1.3 Overview and contribution of this research

The main contribution of the thesis are summarised as follows:

1. A mathematical model framework has been established for a typical residential home energy system, which includes an EV, an ESS, and other residential loads, with grid connection. The EV usage patterns are also considered in this model with driving and parking probabilities calculated from survey data. The practical survey is designed to include driving usage at different time periods. Information such as the driving distance, starting time and duration when the vehicle is away from home, time duration for parking outside and at home, has been collected and processes. This modelling scheme can be conveniently expanded to include components such as PV and SWH systems.
2. Based on the established model, the optimal charging and discharging strategies for EV and ESS are determined for various scenarios under the fixed and the time-of-use (TOU) tariffs. In the case study, the threshold level of the export tariff is calculated, below which the V2G benefit cannot be achieved.
3. One renewable energy option, the solar thermal system, has been included in the optimisation of the residential home energy system, keeping the EV/ESS charging design in the same framework. The benefits of using a solar thermal collector for the end users have been investigated from the economic point of view. Two hybrid options are considered and compared, the combined PV-SWH system and the photovoltaic thermal (PV-T) system. For PV-SWH system, the split of the limited solar panel area between SWH and PV is determined when other DSM factors are optimised under the same design framework.
4. To assess the payback of the above energy optimisation systems, annual cost savings are calculated for three different residential systems. Different appraisal methods are applied and compared to analyse the investment worth of these residential energy household systems. The optimal system choices for the end users are discussed

through case studies, such as EV selection, solar hybrid system selection, SWH panel size selection, indications of the installing costs and so on.

1.4 Roadmap through this dissertation

Chapter 2 reviews fundamentals of DSM, classifications of relevant methods and some current challenges. Optimisation methods for DSM are also briefed in this chapter including problem formulation, optimisation model building process and algorithms of integer programming.

Chapter 3 gives an overview of the fundamentals of EV and V2G technology. The optimal charging management of EVs has been reviewed. Literature review also includes the charging management under V2G and some doubts on V2G technology are raised. In addition, the basics of solar energy and its use in residential household are introduced. The fundamentals of solar thermal model are presented, and studies related to load management for domestic water heating are reviewed.

Chapter 4 builds a mathematical model for a residential household energy system, considering EV, ESS, renewable supply, grid connection and other loads. The design objective with the model is to minimise the end user's energy costs by managing the charging/discharging status of EV and ESS. The design problem can be taken as the individual DSM optimisation problem from the user's interaction with the grid. The battery degradation cost model and the model of uncertain driving probabilities are also developed. Comprehensive case studies are investigated on impacts of different FITs, impacts of different initial SOC and terminal SOC, whether V2G is beneficial to the users. Comparisons are made with typical settings without DSM optimisation.

Chapter 5 expands the study to include controlling of the renewable energy. A household energy system model is developed that also involves solar thermal systems. By controlling the on/off status of electricity back-up system of the solar thermal part, in addition to the EV and ESS charging/discharging status, the end user's cost can be further reduced. Relevant case studies have been investigated to examine the impacts of solar energy on cost reductions such as the hot water temperature, the interaction between residential SWH system and PV system, hybrid PV-SWH system, hybrid PV-T system.

Chapter 6 explores return-of-investment of the household energy system built on the work of the previous two chapters. Several appraisal methods are reviewed, such as payback period (PB), discounted payback period (DPB) and net present value (NPV). They are applied to assess and analyse the investment return period of the energy system with optimised DSM. The annual costs of different types of household energy systems are calculated and compared from financial point of view.

Chapter 7 summarises the contributions and outcomes of this thesis. Future works that can be built upon the findings of this work are also discussed.

1.5 Publications

Journal article:

Yanyi Sun, Hong Yue, Jiangfeng Zhang and Campbell Booth, "Minimisation of residential energy cost considering energy storage system and EV with driving usage probabilities," *IEEE Transactions on Sustainable Energy,* Early Access, September 2018. (DOI: 10.1109/TSTE.2018.2870561)

Conference paper:

Yanyi Sun, Hong Yue, Jiangfeng Zhang and Campbell Booth, "Minimisation of residential energy costs for PV-SWH and PV-T systems," in 12th IFAC Symposium on Dynamics and Control of Process Systems, including Biosystems (DYCOPS2019), Florianópolis, Brazil, April 2019: 1-6. (oral presentation)

Chapter 2 Introduction to Demand Side Management (DSM) and Optimisation Basics

In this chapter, the concept of traditional power grid is firstly introduced in Section 2.1. In order to address the issues faced by the traditional power grid, such as environmental side effects and growing energy demand, the traditional power grid should be evolved and the notion of smart grid is discussed in Section 2.2. In smart grid, the end users play an important role in that the actions of energy consumption can be fed back to the grid operator through the smart metering system enabling local energy demand management; therefore, the fundamentals of DSM, which can help to reduce the end user's cost of energy and air pollution through reducing energy use, is introduced in Section2.3. Furthermore, DSM methods can be classified based on the planning horizon, impact of the applied measures on the customer process and the optimisation model used, which are introduced in Section 2.4. The obstacles and challenges when implementing DSM program are discussed in Section 2.5. Optimisation is a key technique to achieve DSM. The basics of an optimisation model is introduced in 2.6. The general procedure for optimisation is summarised in Section 2.6.1. Then, the details of how to formulate an optimisation model is given in Section 2.6.2. In this thesis, the controlling variables are on-off status of the household devices, so the relevant problem can be formulated as an integer programing problem. One method of integer programing optimisation is introduced in Section 2.7.

2.1 Traditional power grids

Traditional power grids are designed to deliver electricity from producers, which are central power plants, to consumers through high voltage transmission lines. Central power plants usually burn fossil fuel, such as coal, natural gas, and oil, to produce the electricity, for large scale and continuous operation of power grid. However, the environmental adverse effects are serious for fossil-fuel plants, e.g. greenhouse gas emission produced by burning coal, destruction of large areas of land for mining of coal, unpleasant odours of natural gas, and leaks of crude oil under the sea [22]. Therefore, renewable energy sources, such as solar energy and wind energy are widely encouraged to substitute the traditional power sources. In UK, the government targets to deliver 15% of the energy consumption from renewable sources by 2020 [23]. An overall policy for production and promotion of energy from renewable sources in EU has been established, and 20% of the total energy needs with renewables are required to be fulfilled by 2020. In China, the wind power capacity has increased from 0.567GW in 2003 to 91GW in 2013, and the government plans to grow it to 200GW by 2020 [24]. Multiple benefits can be obtained by implementing a variety of renewable energy, such as reduce the demand for traditional energy, reduce air pollution, mitigate climate change, and promote economic development [25]. However, some challenges and barriers exist when synchronising large scale of renewable generation. For example, higher penetration of renewable energy sources with traditional power grids will affect the stability of grids due to the fact that renewable generations are intermittent and uncertain [26]. Therefore, the optimal dispatching of larger scale intermittent resources becomes more critical and the traditional power grids need to be improved to cope with the change of generation. In addition to the change of generation results from environmental stress, traditional grids also need to face other changes on technology, values of society, and economy. Thus, system security, operation safety, power quality, cost of supply and energy transmission efficiency need to be re-examined in order to meet the new requirements of these changes by taking renewables [27]. The traditional grids need to be evolved to smart grid.

2.2 Smart grids

According to [27], "smart grid is an electricity network that can intelligently integrate the actions of all users connected to it – generator, consumers and those that assume both roles – in order to efficiently deliver sustainable, economic and secure electricity supplies. It employs innovative products and services together with intelligent monitoring, control, communication and self – healing technologies".

The goals of the smart grids have been summarised in [28] as follows: provide power quality for the range of needs in a digital economy; accommodate all generation and storage options; enable new products, services, and markets; enable consumers actively get involved; operate resiliently against physical and cyber-attack and natural disasters; anticipate and respond to system disturbances in a self-healing manner; optimise asset utilisation and operating efficiency.

Like the traditional grids, smart grids also consist of four main parts, which are generation, transmission, distribution, and utilisation. The main differences between smart grids and traditional grids are the smart communication and networking, which can help to manage the variability of renewable resources, facilitate access to distributed generation on a high share, balance supply and demand in a manner that is best for the power grid, enable distributed control of both power generation and power, improve the energy system at the side of consumption, optimally schedule the use of loads for both individual and industrial end users and so on [28, 29]. It is noticed that the end users play an important role in the operation of smart grid since actions of consumption can be fed back to the grid operator through smart metering systems thus enabling local energy demand management.

The residential sector is currently a major consumption of electricity in many countries. According to [30], residential sector is the biggest sector of the total U.S. retail sales of electricity, which occupies 38% of total electricity consumption. In EU, the electricity used by households is around 25% of the total consumption [31]. In UK, the residential electricity demand is occupied 30% of total electricity consumption [32]. The house consumption of electricity from one hour to another varies a lot during a day, which can be illustrated in Fig. 2 - 1 using literature data [33]. The electricity consumption reaches a peak point over a certain time period that can induce heavy stress on the grid. Therefore, how to manage and control the energy demand becomes a crucial issue to relieve the grid stress and improve the efficiency of energy use. To address this issue, DSM has been put forward to influence the load with less cost compared to building a new power plant or installing extra electricity storage device. DSM also helps to promote the locally generated energy consumed by local loads.

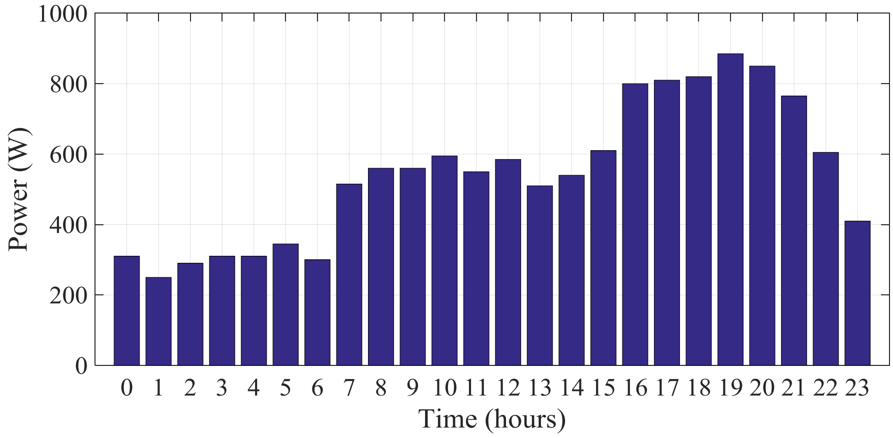

Fig. 2 - 1 An illustration of average hourly load variation during a day [33]

2.3 Fundamentals of demand side management

DSM is traditionally seen as changing the load shape in power system in order to help the energy providers reduce the peak load demand. It is also one of the important functions in smart grid that allow customers to choose from a range of products following their preferences [14] [28]. Key motives of DSM are to reduce the total cost to meet energy demand, and reduce air pollution. In [34], the potential of DSM efficiency improvement has been estimated. The average annual energy savings from the selected DSM technologies are approximately 2,160GWh over a period of 10 years, and considerably reducing CO2 emissions through the selected technologies. Other motives of DSM are to maintain power system reliability or help to reduce the need for network expansion. In [35], a method for assessment of system reliability has been proposed and developed. It suggests that DSM schemes can help to reduce network congestion and improve reliability and quality of network supply.

2.3.1 Architecture and components of DSM frameworks

The fundamental components of DSM can be categorized into end user's domain and smart grid domain. In the end user domain and particularly for residential users, necessary components include local generator, smart devices, sensors, ESS, and energy management unit. Through these components, residential users can manage electricity power for their own usage, provide data for remote control and monitoring, store energy that allow DSM to be flexible, and exchange information with other parts of the system. These components are able to interact with each other, and manage the electric resources based on intelligent DSM schedules [36]. All of these components are connected through one or more home area networks (HANs) within the user's domain. It can be either wired networks or wireless. Then the user's domain is connected to the smart grid domain through wide area networks (WANs), such as cellular networks that can guarantee reliability and quality of service in data transmission. A typical DSM framework for residential home is shown in Fig. 2 - 2.

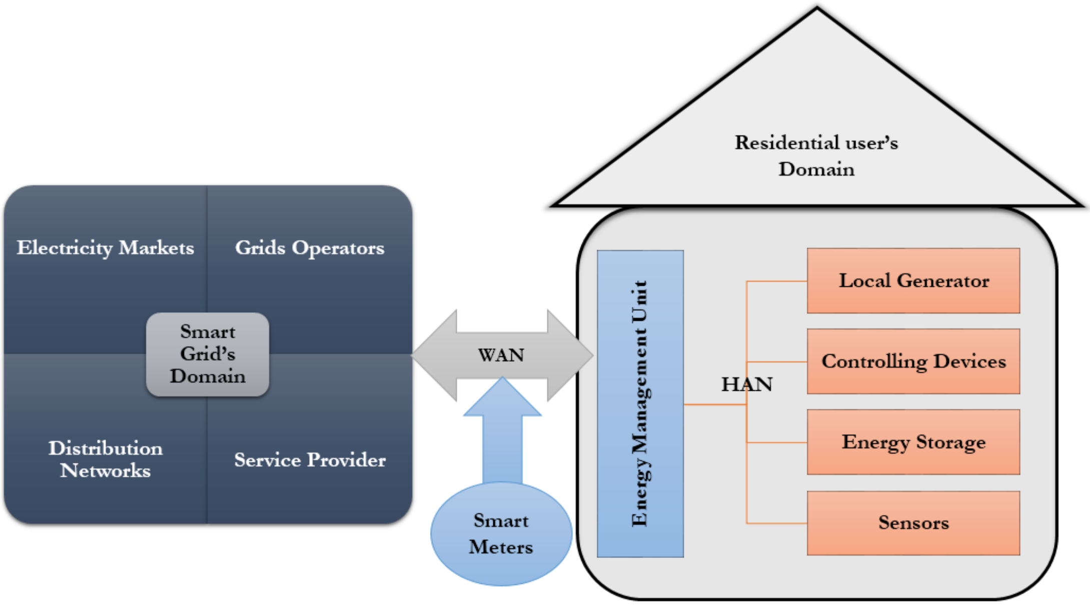

Fig. 2 - 2 DSM framework for residential home systems [36]

2.3.2 Types of demand side management activities

In this section, two categories of DSM activities are introduced, which are energy reduction programmes and load management programmes.

2.3.2.1 Energy reduction programmes

Some of the energy reduction programmes reduce consumer's demand through more efficient processes, buildings or equipment [37]. They include a large number of measures called housekeeping items. Some of these "energy saving tips" can be implemented without extra cost, while others may require significant capital investment.

For example, hot water heating is a major activity in industrial and commercial sectors. Poor boiler operation may result in a significant energy loss, thus improvement of boiler performance is a practical and low cost option for enterprises. Other activities such as improving performance of steam systems, managing the lighting system, and controlling the compressed air system will also contribute to energy savings while keeping the low cost.

The no-cost or low-cost measures can be summarised as below:

a) Sealing and insulation: look for hot air escapes, and failed insulation in floors, walls, doors, windows, fans, vans, heating, electric outlets and so on;

b) Hot water storage tank: limit the temperature of water to a fixed value, use insulating blankets and pipes.

c) Washing machines: only run with full load;

d) Replace incandescent lighting with compact fluorescent lamps (CFLs);

e) Use curtains to insulate sunlight if hot, or let sun in if cold.

However, if some of the measures need to replace the existing equipment or install a new one, significant investment will be necessary and the relevant payback period needs to be considered and investigated, for example, replace old appliances with new and efficient ones; install solar water heater instead of traditional electric water heater (EWH); install double glazing windows.

Another group of commonly used measures of energy reduction programmes are energy management activities, which typically cover the following measures [37]: energy purchasing; metering and billing; performance measurement; energy policy development; energy surveying and auditing; awareness-raising, training and education; capital investment management.

The specific projects of energy management depend on the nature of the organisation, budget, and staff skills. They are continuous process, in which the energy performance is continuously monitored and the efficient use of energy is constantly improved and maintained. Once the top management has been approved in the organisation, an important part of the energy manager's job is to collect and analyse data, and be aware of load profiles or time-of-use for all forms of energy consumption. The load management programmes are needed when the energy manager obtains reliable quantitative information of load profiles through automated measurement and recording equipment.

2.3.2.2 Load management programmes

Load management programmes have been more stable over time than most other customer programmes [38]. From strong load growth, load management can provide significant opportunities for effective DSM that can reduce or postpone use of new generating facilities, therefore the operating cost of energy system can be reduced through changing the load shape [14]. Load management programmes focus on reducing customer use strategically at the time of high utility-system load. The goal is to avoid construction of generation, production, and delivery facilities that only operate for a few hours per year and/or the costly wholesale purchases when customer loads can be shifted or displaced at less cost. There are six generic load shape objectives considered in load management programmes, which are shown as follows [14, 28, 38]:

(1) Peak clipping is a form of load management that focuses on reducing the peak demand to mitigate the burden of grid at peak times. It is a direct load control technique to make reduction of the peak loads, and can help to increase the security of smart grid [14, 28, 38]. The diagram of peak clipping load shape is shown in Fig. 2 - 3.

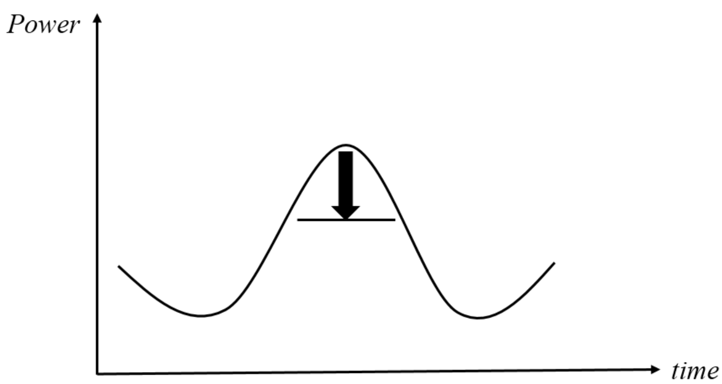

Fig. 2 - 3 Peak clipping [37]

(2) Valley filling is form of load management where the demand valleys are filled by building off-peak capacities. The difference between the peak and valley load levels can be reduced through this technique, and it constructs the off-peak demand by applying direct load control. The technique can be achieved by thermal energy storage that displaces fossil fuel loads[37]. Fig. 2 - 4 shows the diagram of valley filling.

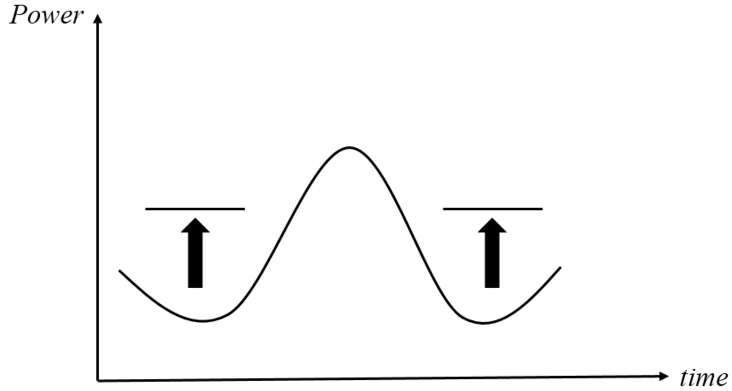

Fig. 2 - 4 Valley filling [37]

(3) Load shifting can shift loads from peak time to off-peak time, and takes advantage of time independence of loads. Load shifting is different from peak clipping because the peak load is present in the overall demand whereas it is removed in the clipping method. Popular applications of load shifting include using storage water heating, storage space heating, coolness storage, and customer loads shifting [37]. Fig. 2 - 5 shows the load shape of the load shifting technique.

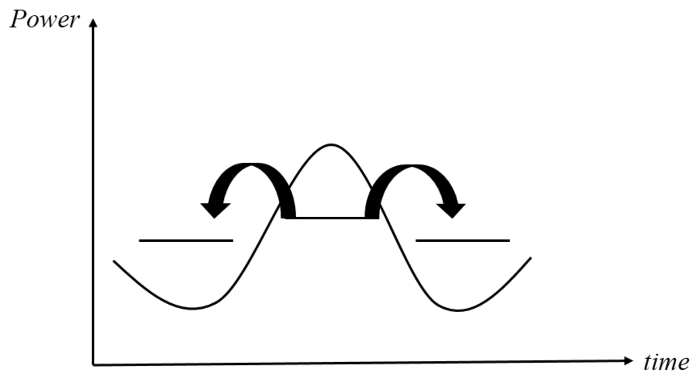

Fig. 2 - 5 Load shifting [37]

(4) Strategic conservation aims to stimulate demand reduction programmes directed at customer consumption in order to achieve load shape optimisation. Examples of strategic conservation usually include weatherization and appliance efficiency improvement [14, 37]. Fig. 2 - 6 schematically represents strategic conservation.

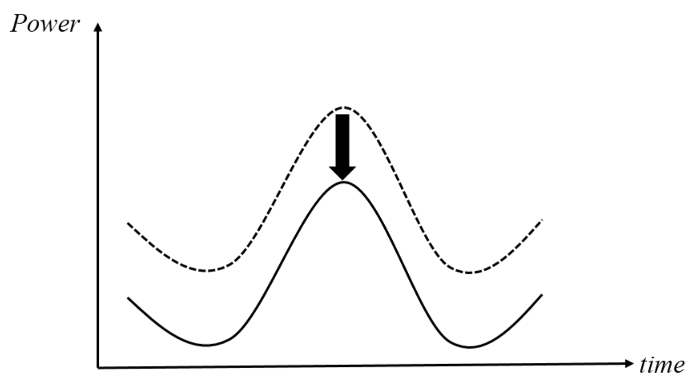

Fig. 2 - 6 Strategic conservation [37]

(5) Strategic load growth is based on increasing the market share of loads supported by energy conversion, storage system or distributed energy resources. It intends to improve customer productivity and environmental compliance while increasing the sale of power for the utilities. The valleys and peaks can be filled and increased, and unsustainable energy practices can be diverted to more efficient practices. This is represented schematically in Fig. 2 - 7[37].

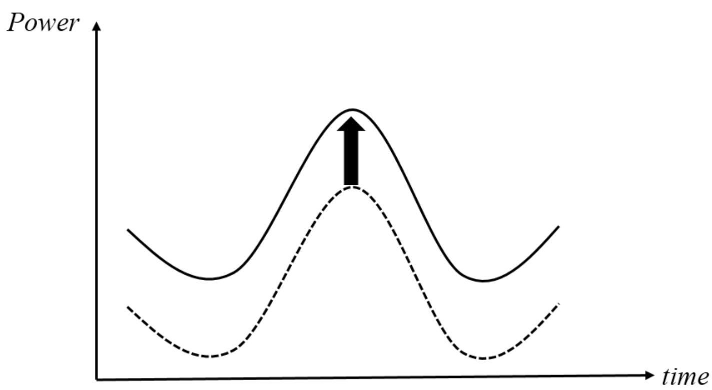

Fig. 2 - 7 Strategic load growth [37]

(6) Flexible load shaping: the load shape can be flexible if customers are willing to change power usage over time for various incentives. The future load shape needs to be anticipated, which includes demand side activities forecasted over the planning

horizon [13]. It is mainly based on reliable smart grid, and the idea is shown in Fig. 2 - 8.

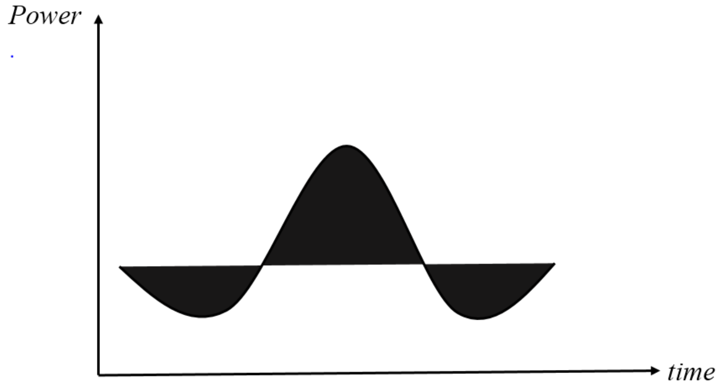

Fig. 2 - 8 Flexible load shape [37]

Among these load management programmes, load shifting is a classic form of load management and is widely applied. The key factor in load shifting is energy storage. In this thesis, three types of loads are directly controlled, which are EV, ESS and SWH. All of these loads have energy storage function. By considering the renewable generation, e.g. PV, and TOU electricity tariff, the load shifting can be achieved. Details of these loads shifting results are shown in Chapter 4 and Chapter 5

2.4 Classification of DSM methods

There are many DSM methods to apply, which can be classified based on the planning horizon, impact of the applied measures on the customer process and the corresponding optimisation model used.

2.4.1 Classification by planning horizon and impact

DSM methods can be classified based on the planning horizon and the impact of the applied measures on the customer process, which include energy efficiency, TOU tariff, and demand response (DR), as shown in Fig. 2 - 9. According to reference [39], the quicker the changes are processed and done, the more unwanted impacts imposed on the customers' processes.

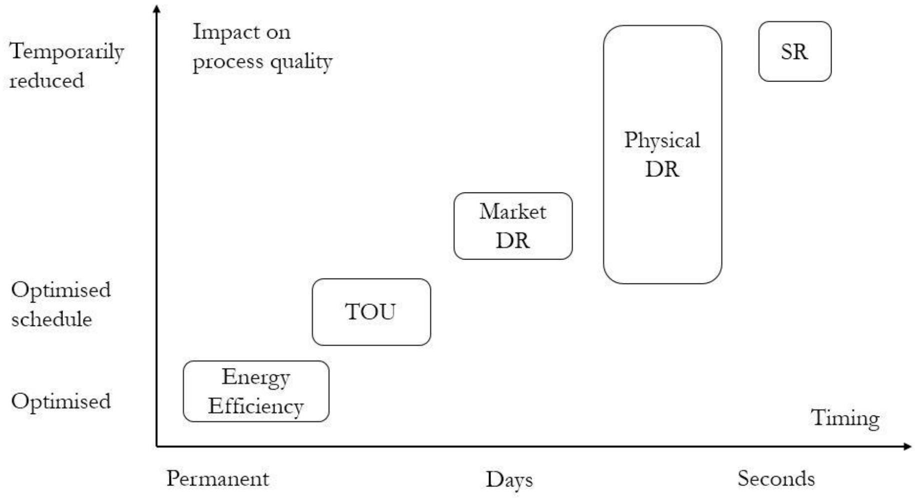

Fig. 2 - 9 Categories of DSM based on planning horizon [39]

It can be seen from Fig. 2 - 9, energy efficiency measures result in immediate and permanent energy and emissions savings, which include permanent changes on equipment or improvements on the physical properties of the system.

TOU tariff increases the electricity price on certain periods of time when the demand is high, so energy consumers pay the actual lower rates for off-peak usage and higher rates for on-peak usage. In addition, users' operating plan is usually defined over the next day period, which is also called day-ahead planning; therefore, some predictions of data, such as energy generation of local sources and devices usage preference for the next day, are required [39].

DR is a form of dynamic DSM. It can be categorised as market DR and physical DR. Market DR includes real-time pricing, price signals and incentives. It relies on certain market places where prices are formed and products are traded. Most of the transactions are done day-ahead. Real-time pricing will not be delayed because the users' plan is re-defined based on real time events and data. Another form of DR is physical DR which can achieve real load shedding for grid relief that cannot be done via prices alone. It will send out binding requests for demand management if grid needs maintenance or line fault happens in parts of the infrastructure [39].

2.4.2 Classification by optimisation models

Mathematical optimisation methods are developed to find out the 'best' values of system design and operating policy variables that will lead to the highest levels of system performance [40]. If DSM systems are classified by the corresponding optimisation model, it can be classified based on user's interaction and optimisation approach [36].

From the perspective of user's interaction, the end users can be either individually managed or jointly managed [36]. If customers are individually and separately managed, the maximised benefit of single end user will be guaranteed. On the other hand, users collaborate in defining their operating plans usually aim to increase the performance of grid or benefit the company. In further classification, the techniques can be selected as either deterministic or stochastic when designing a new DSM optimization model [36]. In deterministic DSM problems, the parameters of DMS systems such as energy prices, renewable generation profile, load curve and devices usage preferences are defined as deterministic variables. In stochastic techniques, they are represented as random variables in order to consider stochastic nature in the decision making process. More details of the optimisation are discussed in Section 2.6.

To sum up, the target objectives need to be determined in the first place before building an optimisation model, e.g., whether customers are individually managed or jointly managed, whether the model benefits grid or customers. Then, an appropriate technique will be selected depending on the types of DSM systems' data. Finally, the time scale of the model needs to be considered. Different planning horizon will lead to different results to the DSM. A classification tree of DSM is presented in Fig. 2 - 10.

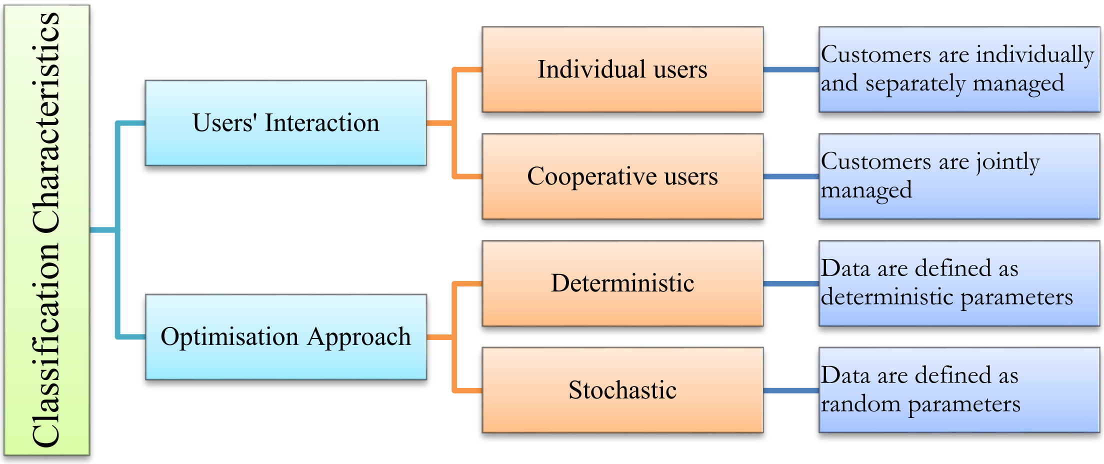

Fig. 2 - 10 Categories of DSM classified by optimisation model [36]

2.5 Demand side management challenges

Obstacles and challenges exist when implementing DSM programme [41]. Firstly, the lack of appropriate market mechanisms in current market structures is a barrier for implementation of DSM. For example, it is argued in [42] that DSM is not comparable to current combustion turbine generating plants though the former is capable of providing more flexible power supply. Another problem when implementing DSM programs is to establish effective communication between the supply-side and the demand-side. This problem has been solved, to some extent, with the advent of smart grid [43].

Furthermore, end-user behaviour is another issue, which compounds the problem of market design for DSM. This is because reactions of the end users are uncertain and complex - they may have many different priorities [41, 42]. The corresponding demand curve is difficult to extract from user behaviours, which depend on many time varying external factors, ranging from the consumers' showering time to cooking time, winter to summer, etc. If EV is plugged-in on residential sector, the vehicle usage needs to be considered in the design of energy management mechanism. Therefore, a proper analysis of the cost benefits of energy use needs to be carried out. A new DSM model for residential home systems should include factors that reflect the benefits and attitudes from the consumer's perspective, such as the cost to the consumer, the ease-of-use, etc.

In addition, how to persuade the consumers to participate in DSM is a problem. Most of the end users are lack of sufficient understanding of the benefits from DSM, especially in developing countries. They are more likely care about whether the DSM strategies can directly bring economic benefits for them; therefore, the DSM strategies should be considered from the end user's perspective in order to attract more end users to participate in DSM. The methodologies for quantification of costs and benefits are imperative to improve the awareness of energy efficiency and DSM programs.

Finally, DSM-based solutions tend to increase the complexity of the system operation when compared with traditional solutions [41]. Other challenges for implementation of DSM are also identified by [37], such as potential losses in power production when implementing DSM programmes, variations in the prices of electricity and other fuels, insufficient data available and so on. Fig. 2 - 11 shows the critical challenges of DSM programs.

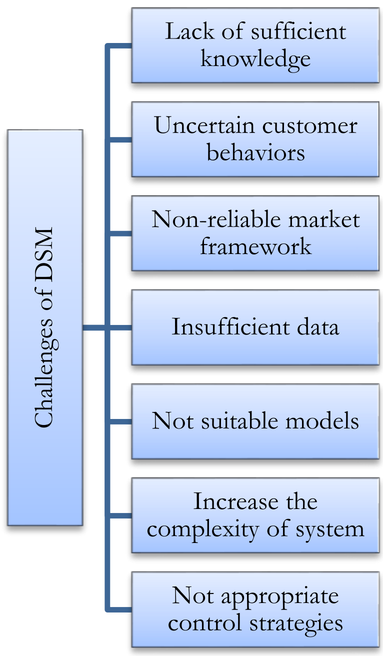

Fig. 2 - 11 Challenges of DSM [37]

2.6 Introduction of optimisation

2.6.1 Optimisation classifications and a general procedure

Optimisation is to obtain the best option among all possible solutions. A basic optimised function can be expressed as follows. Suppose $x_1, x_2, x_3 \ldots, x_n$ are the n decision variables considered, the decision vector can be represented as $\mathbf{X} = \left[x_1, x_2, x_3 \ldots, x_n\right]^T$. If the function is written as $f(\mathbf{X})$ then the optimization problem can be expressed as:

$$\max f(\mathbf{X}), \tag{2.1}$$

to find the point $\mathbf{X}^*$, where $f(\mathbf{X}^*)$ gives the largest value of $f(\mathbf{X})$, and

$$\min f(\mathbf{X}), \tag{2.2}$$

to find the point $\mathbf{X}^*$, where $f(\mathbf{X}^*)$ gives the smallest value of $f(\mathbf{X})$.

An optimisation problem can be classified into different groups following different specifications. It can be classified as deterministic and stochastic (probabilistic). The former has its decision variables and their functional relationships being deterministic. The latter has random variables [44]. An optimisation problem can also be classified into static and dynamic optimisation. In static optimisation, decision variables are independent of time. In dynamic optimisation, the decision variables are time-dependent, therefore, the optimal results are impacted by time-varying factors, for example, the TOU price in cost minimisation of energy system [44].

An optimisation problem can be solved using analytical methods or numerical methods. In analytical methods, calculus is used to get the solution, the optimisation function is often continuous and differentiable. Several techniques can be utilized, such as maxima-minima, partial differentiation, complete differentiation, integration and definite integration. In numerical methods, problems are solved by searching the optimal values at discrete points. They are often used for complex problems [44].

According to [44], the first step in an optimisation procedure is to define the problem. Key aspects include the optimisation objectives or goals, the decision variables, the feasible range of decision variables, and the system restrictions or constraints. The next step is to describe the system using a suitable model. The model can be static or dynamic, deterministic or stochastic, linear or nonlinear by nature. Then, the optimisation problem needs to be solved by a computation method. When the problem is complex, numerical methods are often used to find the optimal solution. Next, the optimal solution and results need to be validated against data or understanding of the real system. The final step is decision-making and implementation, where the optimal strategy is implemented and put to work in practice. In addition, the feedback of the implementation may help to extend the problem for further investigation.

2.6.2 Formulation of optimisation problem

For an optimisation problem, the decision variables need to be identified first. Suppose $x_1, x_2, x_3 \ldots, x_n$ are the n decision variables considered, the decision vector can be represented as: $\mathbf{X} = [x_1, x_2, x_3 \ldots, x_n]^T$. The optimisation performance index is a scalar function of $\mathbf{X}$, $f(\mathbf{X})$. The optimisation problem is then formulated as

$$\mathbf{X}^* = \arg\min f(\mathbf{X}) \tag{2.3}$$

A minimisation function can be expressed as equivalent to a maximisation function and vice versa, by multiplying (-1), which is $\max -f(\mathbf{X})$.

An optimisation problem may or may not have constraints. If the problem requires some limitations in achieving the objective, the constraints need to be designed after building the objective function. There are two types of constraints, which are equality constraints and inequality constraints. The limitations on the behaviour, performance or functionality of the system are commonly represented by inequality constraints. These inequality constraints are classified into two types which are maximum and minimum. Mathematically, the maximum constraints are expressed as less than or equal to $(\leq)$ a certain boundary that limits the system behaviour. The minimum constraints limits the system with a lower boundary $(\geq)$ where a quantity less than the limiting point is not allowed.

After setting up the constraints, the next step is to specify the feasible domains of the variables, which can be called boundary conditions [44]. Three types of the conditions are introduced in the following context, unrestricted condition, non-negative condition, and integer condition. The unrestricted conditions represent that the variables can be selected as any values. The non-negative conditions represent that any values of the variables cannot be negative, and the optimal solutions will be ignored if they are of negative values. These can be mathematically expressed as $x_i \geq 0$. If the variables are not allowed to be fractional, the integer condition is taken, which is expressed as $x \in Z$. In this thesis, the controllable variables are the on-off states of the household devices, such as EV, ESS and SWH, so the boundary conditions of the variables are the integer conditions. More details on how to solve the integer programming problems, either linear or nonlinear, are introduced in Section 2.7. The procedure of formulation of an optimisation problem include the following 4 steps, which are shown in Fig. 2 - 12 [44].

Step1: selecting the decision variables

Step2: formulate the objective function

Step3: setting the constraints

Step4: identifying the conditions of variables

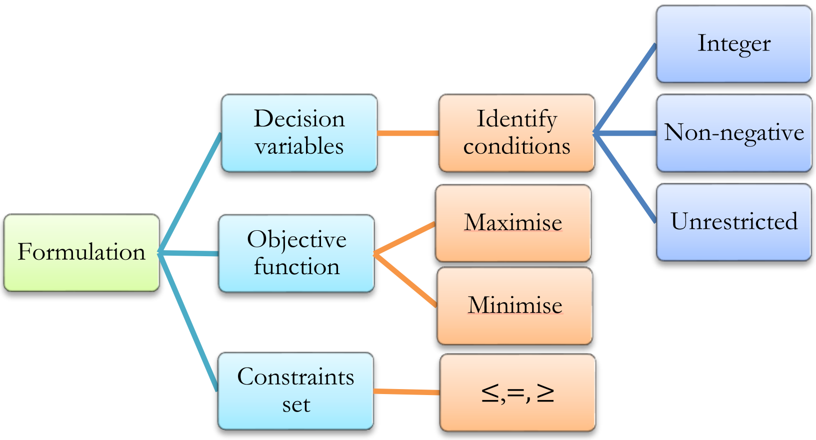

Fig. 2 - 12 Formulation of an optimisation problem [44]

2.7 Optimisation methods

In this thesis, the controlling variables are on-off status of the household devices, such as EV, ESS and SWH; therefore, the relevant optimisation problem can be classified as integer programing problem. In this section, the form of the integer programing problem is introduced.

2.7.1 Integer programming

In many optimisation problems, the decision variables are allowed to be fractional, which is often a realistic assumption [45]. However, for some problems, the fractional solutions are not realistic, for instance, it would be meaningless to have a solution calling for the manufacture of half a table or for the chartering of 1.2 airplanes; the decision variables must be assumed only integer values for these problems, which can be also called inter programming problems [46]. According to [47], integer programming deals with problems of maximising or minimising a performance function of decision variables subject to inequality and equality constraints, applying integer restrictions on some or all of the variables. A linear integer optimisation problem can be expressed as:

$$
\begin{aligned}
&\min f(\mathbf{X}) = \sum_{j=1}^{n} c_j x_j, \\
&\mathbf{X} = \left[x_1, x_2, x_3 \ldots, x_j \right]^T \\
&\text{subject to} \\
&\qquad \sum_{j=1}^{n} a_{ij} x_j \le b_i \quad \text{(i=1,2,...,m)}, \\
&\qquad x_j \text{ is an integer} \quad \text{(for some or all } j = 1, 2, \ldots, n).
\end{aligned} \tag{2.4}
$$

where c_j, a_{ij} and b_i are different constant values.

If all of the variables are restricted to be integer, then the problem is called *pure integer problem*. If some, but not all, decision variables are limited to be integer values, the problem is said to be a *mixed integer program* [47]. A special case that by limiting the value of x_j to 0 or 1, then the model is expressed as:

$$
\begin{aligned}
&\min f(\mathbf{X}) = \sum_{j=1}^{n} c_j x_j, \\
&\mathbf{X} = \left[x_1, x_2, x_3 \ldots, x_j \right]^T \\
&\text{subject to} \\
&\qquad \sum_{j=1}^{n} a_{ij} x_j \le b_i \quad \text{(i=1,2,...,m)}, \\
&\qquad x_j = 0 \text{ or } 1, \quad \text{(for some or all j=1, 2, ..., } n).
\end{aligned} \tag{2.5}
$$

where c_j, a_{ij} and b_i are different constant values.

This type of an integer programming problem is called *binary programming problem*. If all of the variables are restricted to be 0 or 1, then the problem is called *pure binary programming problem* [47]. If some, but not all, decision variables are limited to be 0 or 1, the problem is said to be a *mixed binary programming problem* [47]. For some integer programming problems, the objective function or constraints are nonlinear so they are called nonlinear integer programming. An example of non-linear integer optimisation problem can be expressed as:

$$
\begin{aligned}
&\min f(\mathbf{X}) = \sum_{j=1}^{n} c_j x_j^{\,2}, \\
&\mathbf{X} = \left[x_1, x_2, x_3 \ldots, x_j \right]^T \\
&\text{subject to} \\
&\qquad \sum_{j=1}^{n} a_{ij} x_j \le b_i \\
&\qquad \sum_{j=1}^{n} (x_j^{\,2} + x_j + 1) \le d_i \quad \text{(i=1,2,...,m)}, \\
&\qquad x_j \text{ is an integer} \quad \text{(for some or all } \mathrm{j} = 1, 2, \ldots, n\text{)}.
\end{aligned}
\tag{2.6}
$$

where c_j, a_{ij}, b_i and d_i are different constant values.

In this thesis, the objective is to minimise the end user's household energy cost, where the decision variables are charging and discharging of batteries, and on/off status of electrical appliance; therefore, the problem can be expressed as integer programming problem. An intelligent method, GA, is employed to solve the optimisation problem.

2.7.2 Genetic algorithm

Genetic Algorithm is a type of evolutionary algorithms that are inspired by the process of evolution in human and animal life. It is developed by John Holland and his collaborators in 1960s and 1970s [48]. The basis of the GA corresponds to the process of Charles Darwin's theory of natural selection [49, 50]. All livings carry the gene information to build cells and pass the genetic traits to offspring. If the inherited genes make offspring fit and strong, they are more likely to be passed to the next generation. On the contrast, offspring with poor inherited genes is more likely to die and not reproduce. Therefore, the species who carry the good genes become more successful and stronger to suit the environment. The main contribution of Holland's work demonstrates that rapid improvements of bit strings could occur under certain transformation with an appropriate control structure, and GA would tend to global convergence even in large and complicated search spaces [51]. GA has been developed and applied to a wide range of optimisation problems, such as graph colouring, pattern recognition, financial markets, multi objective engineering optimisation [52]. The GA for an optimisation problem is based on binary coded genetics, which means an optimisation function will be encoded as arrays of bit strings to represent chromosomes. Selection of their fitness, and other operations of strings are determined by genetic operators. The procedure of GA can be summarised by the following steps [49, 52, 53]:

a) encode the objective function;

b) define a fitness function;

c) create a population of the individuals;

d) execute the evolution cycle or iterations by evaluating the fitness of all the individuals;

e) create a new population by performing crossover and mutation;

f) reproduce fitness-proportionate;

g) replace the old population and iterate the process using the new population;

h) repeat step d) to step g) until finding the optimal solution;

i) decoding the optimal solution to the required range of decision variables.

In this work, the optimisation problem is to minimise the end user's energy cost, where the decision variables are the charging/discharging status of EV and ESS. So, the problem can be expressed as a binary integer programming problem. Unlike linear programming problems, the integer programming problems are difficult to solve. Several traditional algorithms could be applied such as cutting-planes and branch and bound programming; however, they are not both fast and reliable at the same time when dealing with the complex problems. Compared to the traditional optimisation algorithms, there are many advantages of GA. For example, it is conceptually simple, and no gradient information are required in the algorithm. It can be used to adapt solutions to changing circumstances, therefore it is robust to variations in the environment. Furthermore, GA has the ability to deal with complex problems, and it can deal with various types of optimisation problems whether the objective functions are stationary or non-stationary, linear or non-linear, continuous or discontinuous, integer or real. In GA, all points of a population act like independent agents, they can be carried out in several processors, and the population can explore the searching space in many directions simultaneously. Different variables can be manipulated at the same time and a GA algorithm is inherently parallel in searching [52, 54, 55]. Also, the convergence of GA in the sense of probabilities has been widely used in practice. Matlab has a built-in function for GA, which is applicable to mixed integer nonlinear programming problems. Thereofore, GA has been selected to get the solution.

2.8 Summary

In this chapter, the smart gird is introduced, in which the end users play an important role. DSM can help the grid operator manage the end user's demand, through which the end user's energy cost and air pollution through can be reduced. Classifications of DSM methods have been presented based on the planning horizon, impact of the applied measures on the customer process and the optimisation problems. The obstacles and challenges when implementing DSM program are discussed.

The formulation of the optimisation problem is crucial for DSM. The basics on how to build an optimisation problem and get the solution are introduced. The optimisation problems in this thesis work are categorised as integer programing problem. The integer programming optimisation and the GA algorithm are briefed.

Chapter 3 Smart Home Energy System with EV and Solar Water Heater: a Review

EVs have become popular in the past decade in order to reduce greenhouse gas emission in transportation systems. Many countries have established schemes targeting to replace the combustion vehicles with EVs in order to achieve zero emissions after a few decades. It can be predicted that EVs will eventually become the most common vehicle for households in the future. In residential home energy systems, SWH can be utilized to replace EWH and satisfy the daily hot water demand, which can help the end user to reduce the electricity consumption. Since the switching status of EV and SWH can be controlled, the impacts of their operation on energy saving should be investigated from the DSM perspective. In this chapter, the basic scheme and controlling strategies of EV and SWH systems have been reviewed. A new technology on EV discharging, V2G, is introduced. Section 3.1 presents fundamentals of EV and V2G technology. Some studies related to the optimal charging management of EVs are reviewed in Section 3.2. In Section 3.3, the studies of EV charging and discharging strategies involving V2G are reviewed. The fundamentals of SWH is presented in Section 3.4, and relevant existing studies of load management for domestic water heating is reviewed in Section 3.5.

3.1 Introduction of EV and V2G

3.1.1 Fundamentals of electric vehicle

An EV uses one or more electric motors for propulsion instead of a traditional petrol/diesel engine. A rechargeable battery that can be charged by common household electricity is used to store the energy to power the electric motors. When the accelerator pedal is pressed, the power is converted from the DC battery to AC for the electric motor; then the accelerator pedal sends a signal to the controller which adjusts the vehicle's speed by changing the frequency of the AC power from the inverter to the motor. The motor connects and turns the wheels through a cog. When the brakes are pressed, the motor becomes an alternator and produces power, which is sent back to the battery. The key components of an EV and a schematic are shown in Fig. 3 - 1.

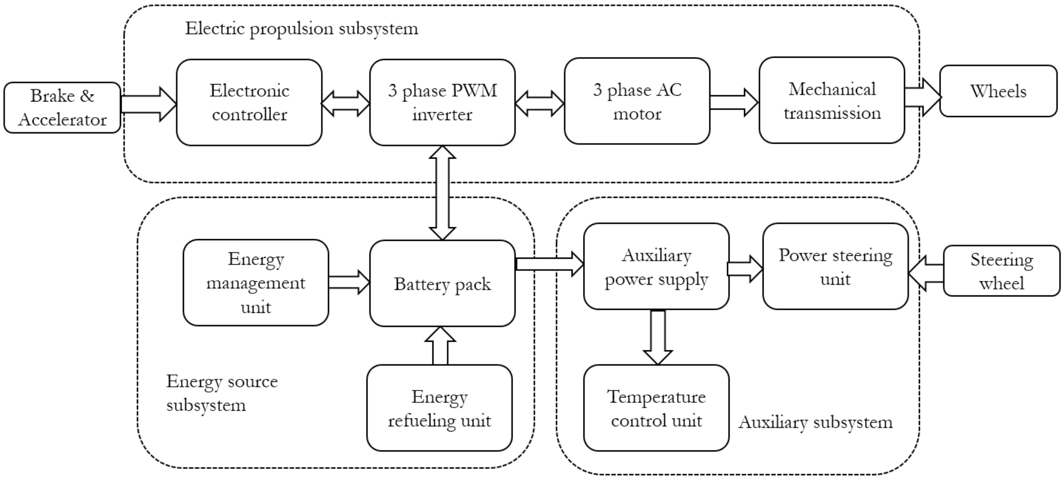

Fig. 3 - 1 A schematic of EV [56]

The early type of electric motor was invented by Anoys Jedlik who created a small electric model car by his new motor in 1828 [57]. In fact, the transportation power is dominated by petroleum-derived fuels for a long time because of the high cost, heavy weight, and short driving range of battery EVs. However, batteries are becoming cheaper and lighter in weight, and the traditional liquid fuel will be eventually replaced because EVs can help to reduce adverse dissemination when they are combined with a broad use of renewable and carbon free energy sources in the transportation sector. EVs can be categorised into several types: hybrid EVs (HEVs), plug-in hybrid EVs (PHEVs) and battery EVs (BEVs) [58].

HEVs are powered by two drive systems, which are gasoline engine with a fuel tank and electric motor with a battery. They start off using the electric motor, then the control system will switch to gasoline engine if vehicle speed rises. Both systems can turn the transmission at the same time, and are controlled by an internal controller which ensures the best running for the driving conditions. HEVs cannot be charged from the electricity grid. All of the electric energy is generated from the gasoline and from the vehicle's own braking system which is called regenerative braking. This is a process that the heat generated from brakes is converted to electricity form to drive the electric motor [58, 59].

PHEVs are also powered by both of the electric motor and the internal combustion engine. However, the battery, which drives the electric motor, can be plugged into the power gird and recharged. The owners can achieve more fuel cost savings from PHEVs than traditional HEVs because of the use of electricity from grid [58, 59].

BEVs are not supported by traditional combustion engine and only powered by electric motor and battery, so they must be plugged into the grid or other external source of electricity to charge the battery. Like other types of EVs, regenerative braking can also help BES to recharge its battery. The pros and cons of different types of EVs are shown in Table. 3 - 1[58, 59].

Table. 3 - 1 Pros and cons of different types of EV[58, 59]

EV types	Pros	Cons
HEVs	➢ Longer driving distance than BEVs ➢ Less fuel consumption and emissions than traditional combustion vehicles	➢ Complex mechanical design of both gasoline engine and electric motor ➢ Still produces emissions ➢ No ability to charge at home ➢ The costs of operation are more expensive than BEVs but less than traditional gasoline vehicles
PHEVs	➢ Longer driving distance than BEVs ➢ Less fuel consumption and emissions than traditional combustion vehicle ➢ Can be partially charged ➢ Very simple mechanics	➢ Still produces emissions ➢ The costs of operation are more expensive than BEVs but less than HEVs.
BEVs	➢ No emissions ➢ Ability to charge at home ➢ Fast and smooth acceleration without noise ➢ Much lower cost of operation	➢ Shorter driving distance than other vehicles ➢ The price of the vehicle is slightly more expensive than other similar level vehicles

3.1.2 Briefs of vehicle to grid technology

The core part of an EV is its battery pack, which could be used as energy storage device. When the electricity in this energy storage is allowed to flow from vehicles to the power grid, it is called "vehicle to grid (V2G)" technology. V2G technology refers to the capability of controllable and bi-directional electrical energy flow between a vehicle and the electrical grid [60]. It also includes vehicle to home or vehicle to building that EV's battery can be used to service household or local building's electrical load without transferring to the power grid.

Some benefits could be achieved through V2G technology. From the perspective of grid or company, V2G can help to provide power to the grid when the demand is high, and charge the battery of EV when the demand is low. Therefore, both of peak shaving and valley filling can be achieved if charging and discharging of EV are properly controlled. Through the V2G technology, EVs can also be considered as an ESS to suppress the oscillation and peak deviation in grid frequency [61]. In addition, the charging station of EVs can be utilised as renewable energy storage, which can smooth the intermittency of renewable power generation and support the increased use of renewable energy. Therefore, there is no need to build the new energy storage facility and the financial cost of the grid's company can be reduced. On the other hand, EV owners may obtain rewards if the grid company provides an attractive incentive scheme to encourage the participation of V2G. Also, V2G could play a vital role during power outages. It can help the owners support the critical electrical appliances during the outage period.

There are still some doubts when applying the V2G technology, such as whether the battery degradation could be compensated by the power selling price or market incentives, and whether the EV owners are willing to discharge their EVs at a certain time.

3.2 Optimal charging management of EV

In some recent studies, the potential impact of EV charging on distribution network has been investigated, and optimised charging strategies have been developed in order to relieve the pressure on the network. A mathematical model is proposed in [62], which aims to determine the optimal size and site of PHEV charging stations in distribution networks. The objective is to maximise benefits of the distributed system. Several constraints on power qualities have been involved such as the power flow balance, the voltage limits, the thermal limits of substations. The test results show that not only the cost of the distributed system can be reduced through the optimisation, but also the voltage and the load profile can be improved. Though load and price uncertainties are considered in their work, the uncertainty behaviours of the customer, such as departure and arrival time of EV, are lacking. Another study [63] proposes a linear programming method, which controls the charging rate of individual vehicles in order to maximise the total power that can be delivered to the vehicles. In order to ensure that the operation is within network limits, voltage and thermal loading constraints are also involved. Results show that high penetrations of EV can be accommodated on existing residential networks with little or no need for upgrading network infrastructure. This study assumes that all EV batteries have the same capacity of 20kWh, and the objective was to return an average state of charge (SOC) of 99.9% for all EVs. The battery capacities of EVs are, however, different from each other in practice. The higher-capacity EVs could not be guaranteed with charging to the same SOC level as the lower - capacity EV. A decentralised online algorithm is proposed in [64], in which each EV charging rate is calculated and guided through the updating valley level of the utility. Simulation results show that power loss can be reduced, and the value of the online solution is larger with higher penetration compared with the offline solution. Another charging control method is proposed in [65] for the situations where frequent communication with EVs is not possible, and the ideal valley filling can be achieved. In this work, modelling of EV arrivals and departures as random events are also lacking, and the battery state of health is not considered. In [66], EVs are controlled as the DR in order to mitigate the intermittent effects of wind generation. It shows that the grid frequency regulation can be improved, and the cost reduction of the generation can be achieved with 99.5% charging of EVs. The battery capacity of all EVs is assumed to be the same as 16kWh. Also, this study assumes that the charging of EVs are free to control to support reserves and no rewards are given to EV owners. This can be an issue when controlling the EVs as the DR, since the willingness of customers' participation must be considered in practice.

There are studies aiming to minimise the EV charging cost either for the charging station or for the EV owners. For example, a mixed-objective formulation from both system and customer perspectives is proposed in [67], which shows that the valley filling can be successfully achieved for the system and the customer's charging cost can be minimised under TOU rate structure. The paper indicates that the results are validated using actual driving behaviour data from the National Household Travel Survey. In [68], a dynamic programming framework is proposed to determine an optimal charging strategy at parking-lots. The driving behaviours including the arrival time, the departure time and the arrival SOC are modelled as Poisson process. The method has been verified that it can significantly decrease the energy cost for a commercial parking-lot. A charging scheme in the parking station is presented in [69], which satisfies EV charging and coordinates DR programs. In this study, uncertainty arrival behaviours of vehicles are represented as a Gaussian model, and four types of battery capacities are considered. The results show that the proposed approach can help to maximise the EV numbers for charging and minimise the monetary expense. However, EV may not always be charged at parking-lots, and the EV parking time at home is much longer than parking outside for vehicle owners during 24 hours period. The Poisson distribution or the Gaussian distribution can be inadequate to describe the probabilities that EVs are parked at home.

With integration of renewable energy and ESS, designs of EV charging stations are proposed considering EV car park and renewable resources [70-75]. It's been shown that the utilisation of renewable energies, ESS and DSM would reduce the impact on the grid and increase the profits of the parking lots. A scheme for a PV-powered EV charging station is proposed in [76], in which EVs are classified into three types, premium, conservative and green. The premium EVs are ensured that they are charged to the maximum possible states whenever the EVs leave the charging station. Conservative EVs are charged to the state as set up by the owners. Green EVs are similar to the conservative EVs except that they are allowed to discharge the power. The objective is to reduce the effect of intermittency of the generation and the cost of energy trading for charging station. Simulation results show that increasing penetration of green vehicles can reduce the total energy trading cost by 85% in summer and 82% in winter. Green vehicle owners' charging cost can also be reduced between 42.7% and 49.4%. However, each discharging of the green vehicle will result in additional battery degradation cost, which needs to be considered in the calculation of the owners' charging cost. Another optimisation strategy for EV charging could achieve 51.52% cost reduction for a single EV [77], but the cost of battery degradation and the EV driving behaviours are not considered.

3.3 Optimal charging of EV involving V2G technology

V2G has been considered in many EV charging scenarios. Recent studies on V2G control and optimal charging strategies have focused to reduce the power load fluctuation, frequency fluctuation, voltage variation and uncertain generation of renewable energy. A decentralised V2G control method to suppress frequency fluctuation is proposed in [78], where a battery SOC holder control strategy is presented to maintain battery residual energy, and a frequency regulation charging method is applied to schedule EV charging and provide frequency regulation. In another study [79], a new supplementary load frequency control (LFC) method is proposed using EV and heat pump water heater (HPWH) as controllable loads. This new LFC method can effectively suppress frequency fluctuation, and reduce the required battery energy storage system (BESS) capacity. To shave peak load and compensate uncertainties of renewable generation, scheduling schemes for V2G operation have been proposed [80-82], with the aim to smooth the fluctuation in load profiles and improve the operation efficiency and grid security. It concludes that V2G can support the grid to shave the peak demand and reduce grid operational costs under suitable energy policy strategies.

Other studies of optimal charging/discharging control of EV concentrate on the cost/benefits of Grid Company or end user. For example, an optimal scheduling of EV charging and V2G at household level is given in [83], which takes into account the cost of battery degradation and price uncertainty. Results of the case studies show that V2G will not happen if the battery degradation cost is larger than the benefits from the grid company. If the battery cost is low and the degradation cost is close to zero, V2G could be attractive to the end users. Therefore, the degradation characteristics play an important role in evaluation of the degradation cost, V2G application, and the pattern of EV charging. Though the relevance of the battery degradation has been revealed, quantitative analysis of the charging-related cost and vehicle usage are missing.

An optimisation charging model proposed in [84] is used to minimise the total energy cost, comprising of V2G integration and DR strategies. The results show that 58% cost reduction can be achieved through the proposed strategy, and meanwhile the consumption load is restricted by peak power limiting DR. However, the battery degradation costs are not considered in their model. In [16], smart charging of EV and V2G is performed to increase the self-consumption of PV from 49% to 87%, and the demand peaks are decrease by 27%-67%. This study also reveals that battery usages will be dramatically increased if V2G is applied; therefore, the benefits of V2G needs to be weighed against this issue. An optimal charge scheduling is proposed in [85] considering V2G technology and relevant battery wear cost. The main objective is to minimise the total charging when the battery degradation costs due to V2G are included. Their results show that the reward value under the assumed FIT can cover the degradation cost, and could encourage the EV owners to participate in V2G program. However, the minimum assumed FIT value, $0.2/kWh, is too high compared with the realistic value. According to the government's report of UK, the FIT is £0.0485/kWh, and the electricity price is around £0.16/kWh.

There are doubts on the economic viability of V2G, primarily due to the high cost of discharge to the grid; this is often related to factors such as battery degradation, expensive battery pack and low FIT. V2G service can also lead to reduced life-cycle of an EV. Power aggregators should operate either on pay-as-you-go basis or provide consumer with advanced cash payment in order to attract more EV owners participating in V2G [17]. The rate of return for V2G is not always sufficient to induce widespread V2G participation due to connection capital costs, electricity purchase costs, and battery discharging degradation costs [18]. The EV's battery pack is likely to be replaced more often when V2G service is applied.[19]. Another optimisation investigation in [20] suggests that the battery aging cost induced by V2G exceeds the revenue brought from V2G, and the substantial subsidies are needed to trigger V2G service.

3.4 Solar water heater (SWH) technology and applications

In this section, the basics of solar energy and typical applied technologies including photovoltaic (PV) and solar water heater (SWH) are introduced. The fundamentals of SWH are presented. The benefits, drawbacks and effects on use of SWH are discussed.

3.4.1 Solar energy

Currently, the global electricity consumption is increasing [86]. Large scale power plants usually burn fossil fuel, such as coal, natural gas and oil, to generate electrical power, which induce huge environmental side effects. These drive development for the renewable energy sources, such as wind, solar, wave and tidal, hydropower and biogas. Among these sources, solar energy is more attractive than others due to its abundance and free of cost all across the globe. It is radiant light and heat received from the sun harnessed on earth that has been recognised as the most important renewable energy source [87]. It is considered as the source of all the energy for life in the world. Technologies to utilise the solar energy have been invented, such as solar heating, solar thermal energy, and photovoltaics. In 1890s, the first commercial SWH was made and sold in USA, and SWH is the most worldwide installed solar thermal systems for heating water by the end of 2013 [88-90]. In 1912, the first solar thermal power station was constructed by Shuman in Maadi. In the 1950s, the first commercial PV cells, which can be utilised to convert sunlight into electrical energy, were invented at Bell Labs [91]. As the technology advances, the conversion efficiency of solar PV and SWH become higher, and the instalment prices are reduced. They have been widely used for household applications. Both PV and SWH can help to reduce the electricity consumption of the end user. For example, the end user can install the PV panel to directly generate the electricity power for their own usage. SWH can be utilised to replace EWH and satisfy the daily hot water demand, which can also reduce the electricity consumption. Compared with PV, SWH is much easier to be controlled due to its switching on-off characteristics. In this thesis, the PV generation is considered as a given fixed parameter and SWH is set as the decision variable.

3.4.2 Solar water heater basics

SWHs collect the solar radiation and transfer the energy for water heating. It combines five basic components which are solar thermal collectors, heat transfer system, storage system, control system, and auxiliary hot water system. Solar thermal collector is a device to collect the heat by absorbing solar radiation. Then, the heat energy is absorbed by the heat transfer fluid, such as water, non-freeze liquid, or air, and transferred to heat in the domestic hot water through the heat transfer system. The storage system is used to store the thermal energy in a water type and supply daily hot water consumption. The control system is used to manage the collection, storage, and distribution of the thermal energy. Since hot water peak demand is usually in the morning or late evening and does not coincide with times of maximum solar radiation, the auxiliary hot water system is necessary to guarantee the hot water demand when solar energy is not sufficient. This is typically a conventional electric resistance to heat the water [92, 93]. There are two types of SWHs depending on the way the heat transfer is transported: passive systems, and active systems.

The passive systems can also be called natural circulation systems that occur by natural convection and no pumps are employed. They can be further classified into direct and indirect types. In a direct system, the potable water is heated directly in the collector.

In an indirect system, the potable water is heated by the heat transfer fluid. Fig. 3 - 2 shows a classical passive system [93].

An active system can also be called forced circulation system that use pumps or fans to circulate the heat transfer fluid through the collector. Similar to passive systems, active systems can also be direct or indirect. The direct active systems use a pump to circulate water directly through collector and into the storage tank, which are usually applied in areas that the temperature of climates do not freeze the water. For the areas where freezing temperatures occur, the indirect active systems will be applied that use pumps to circulate heat transfer fluid through the collectors; then, the heat energy will be transferred from the fluid to the domestic water supply trough heat exchangers. The active systems are usually more expensive than passive systems, and more difficult to retrofit in houses. Fig. 3 - 3 shows a schematic diagram of a direct active system [93].

In this thesis, the passive system is applied because it is less expensive than active system. In addition, it is more reliable and easier to maintain due to there are no electrical components involved and do not rely on pumps and controllers.

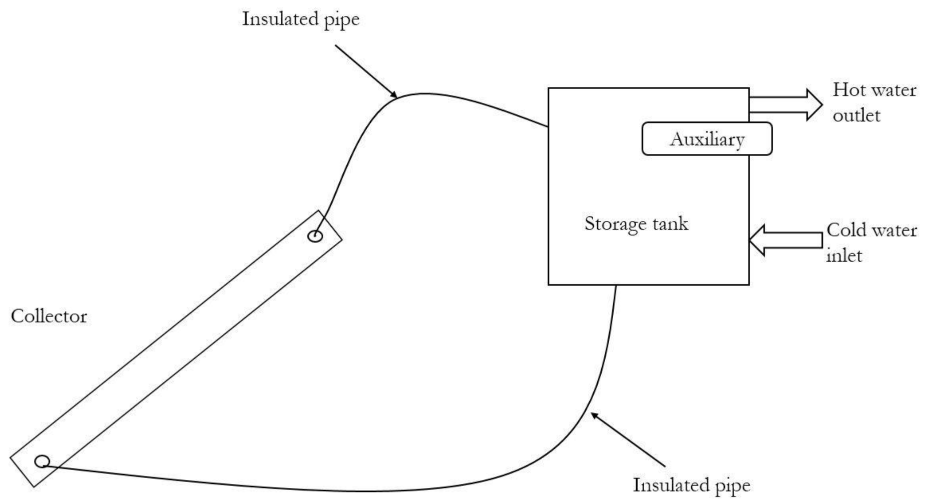

Fig. 3 - 2 Diagram of a passive SWH [93]

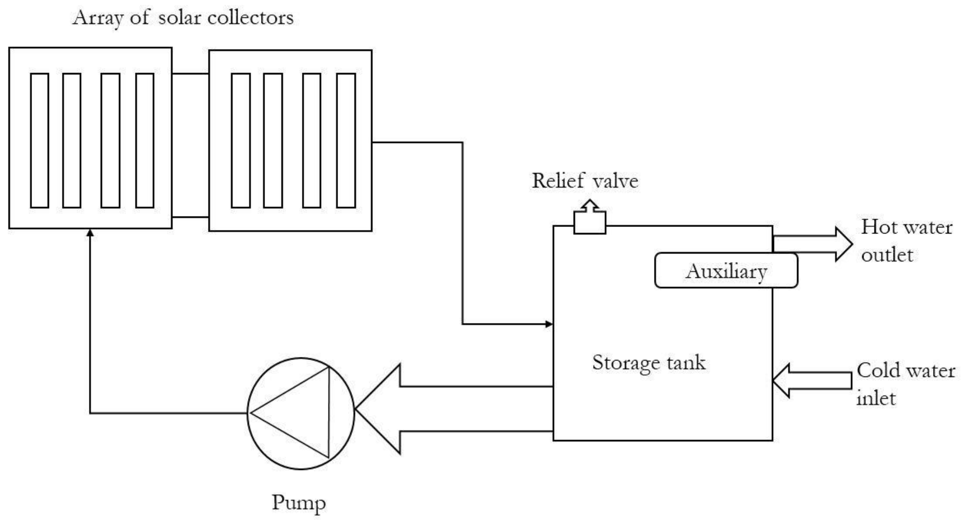

Fig. 3 - 3 Diagram of an active SWH [93]

3.4.3 Benefits, drawbacks and effects on use of SWH

Since SWH was invented, the potential impacts of its application have been investigated from many studies in different countries, such as the reduction of greenhouse gas, cost savings, payback period, and some drawbacks. In this subsection, the use of SWH and its applications have been reviewed.

The potential application of SWH is investigated in Turkey [94]. It is found that SWH market is still strong without incentives by government. The major factors, which influence the popularisation of SWH, are government financial incentive program, payback period, availability of local dealers, and climatic conditions. The market potential and development of SWH in Algeria is discussed in [95]. It shows that SWH systems have not been sufficiently developed in Algeria due to the availability of natural gas at low price, and the SWH devices which are imported from EU are too expensive. SWHs can be used to reduce peak electricity demand, save on carbon emission, and improve householder's standard in South African [96]. However, householders may abandon using SWH if there are no clear benefits within a few months, or if technical problems occurred. The water used will be increased for users who use heater frequently although the electricity bills can be reduced. This may not be an issue for areas with abundant water resources, but it could be a big issue for the water-scarce area [96]. In Iran, one direct effect on the use of SWH is environmental issue, and the financial support from the government has the most influence on SWH market [97]. The potential benefits from using SWH in Zimbabwe is discussed in [98]. It is demonstrated that the electricity peak demand in winter and the final energy demand can be reduced by 13% and 27% respectively, assuming a 50% penetration rate of SWH potential demand, and SWH can help to save up to $250 million in energy cost, and the CO2 emissions can be reduced by 29% over the 25-year period. In Brazil, the reduction of carbon dioxide while using SWH is assessed, and compared with electric showers [99]. It shows that SWH is not useful in hot climactic regions because these areas require much more cooling demand than hot water demand. In another study on SWH use in Brazil [89], the influence of human behaviour is considered. The benefits of SWH in low-income families vary depending on the users and the use of SWH technology. Lack of technological understanding and unable to mix the hot and cold water efficiently become the major factors affecting the use of SWHs. The policy measures are evaluated in Japan on the spread of PV and SWH to reduce carbon dioxide emission from residential sector [100]. The factors that can influence consumer's preferences such as installation cost and energy prices are considered. The public perception must be improved on the fact that the carbon dioxide emission can be reduced considerably by using SWH, and reducing the initial cost is more effective than reducing operating expenditure for carbon dioxide reduction in case of PV.

Two pathways to low carbon energy, SWH and PV, are compared in China [101]. Although SWH technology has received less financial and political support from the central government compared with PV, it can also contribute a lot to low carbon energy since it is applied everywhere across the country, especially in rural areas. The analysis of the comparison between PV and SWH in China is illustrated in [102], with a focus on the cost and benefit for users. The optimal SWH setting area is recommended to be 3-4m^2 for each residential home. The study shows that only when the solar panel's area is larger than 6m^2, PV can utilise more solar energy than SWH.

The payback period of SWH in Malaysia and Taiwan are investigated [103] and [104]. Factors of cost and benefit from financial perspective are taken into account. The reduction of harmful gas with SWH application is reported in [103], where it presents that promoting the use of SWH can save large electricity consumption for Malaysia. By comparing SWH and the traditional EWH, it is found that the payback period is shorter if the EWH is substituted by SWH [104].

The benefits, drawbacks and the impacts of SWHs are summarised in Table. 3 - 2.

Table. 3 - 2 Benefits, drawbacks and impacts of SWH's application

Benefits	Drawbacks	Factors influencing its application
➢ Reduce peak electricity demand ➢ Reduce carbon emission ➢ Improve householder's life standard ➢ Reduce final energy demand ➢ Payback period is shorter ➢ The market is still strong without government incentives	➢ The purchase cost is expensive if it is exported from EU ➢ Users may abandon it for lack of clear benefits or technical problems ➢ Not very useful in hot climactic areas ➢ May result in higher water consumption ➢ Not competitive if the natural gas price is low	➢ Government financial incentive programme ➢ Payback period ➢ Availability of local dealers ➢ Climatic condition ➢ Initial installation cost ➢ Energy prices ➢ Environmental and technological understanding from customer perspectives

3.5 Load management for domestic water heating

Water heating is one of the major energy consumption all around the world [105]. It occupies 11% of the total residential energy consumption in USA, 14% in EU, 22% in Canada, 25% in Australia and Russia, 30% in Japan, 29% in Mexico, and 27% in China. One traditional way to heat the water is to use EWH. As its operation can be interrupted and the switching status of EWH can be shifted in time, control of EWH may have a large DSM potential. An optimal operation scheduling of EWHs under dynamic pricing is proposed in [106]. Simulation results indicate that total energy cost is reduced around 30% for guaranteed water temperature of 60℃. The energy cost decreases with higher upper temperature set point because the higher temperature set point leads to higher thermal energy stored in hot water in tank. The optimal scheduling enables EWH to warm the water during the lower energy prices period. In [107], an optimised control of the domestic hot water heaters for DSM is implemented and tested, and it shows an averaged reduction of cost approximately of 12%.

According to the daily hot water usage data from UK government report [108](Fig. 3 - 4) , the peak period of hot water usage is between 7:00am to 9:00 am in the morning. The daily solar radiation data are selected from the area of Glasgow in UK, which are sourced from [109], as shown in Fig. 3 - 5. It can be seen in conjunction with the daily solar radiation curve in Fig. 3 - 5 that the hot water can be heated by solar radiation during the peak period if EWH is substituted by solar thermal type of heater such as SWH; therefore, less electricity energy will be consumed and the total energy cost will be reduced further.

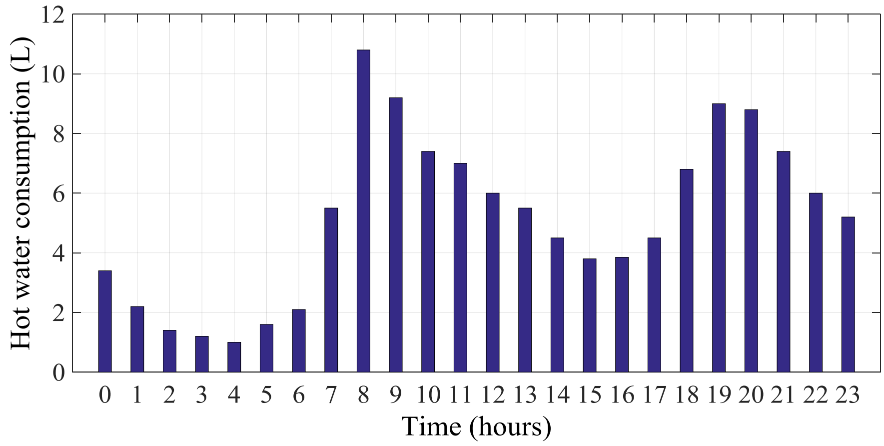

Fig. 3 - 4 Average daily hot water consumption [108]

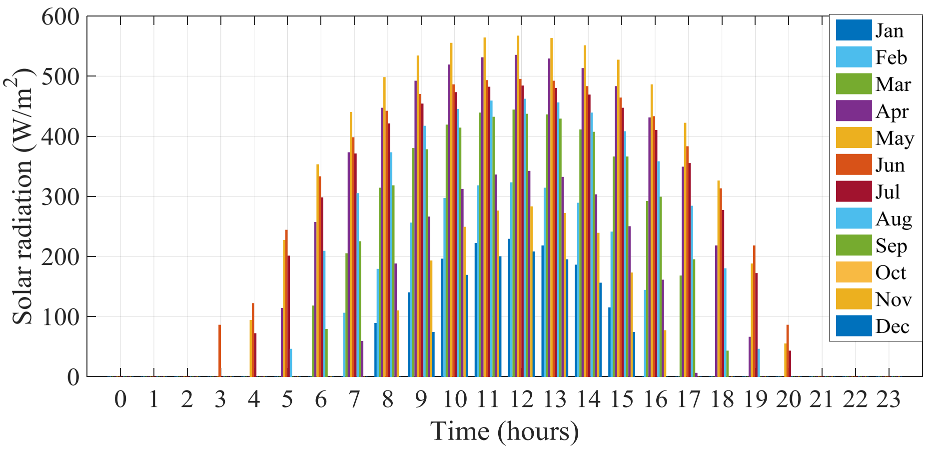

Fig. 3 - 5 Average hourly solar radiation in each month [109]

The effects of disconnections of residential water heaters are examined in [110], which indicates an additional averaged consumption increase after the disconnections due to the payback effect. Thus, an optimal scheduling with the constraint of a smooth load curve is needed. The influence of electricity consumption on the performance of SWH is considered to be huge [111]. How to optimally control the SWH and other residential loads for DSM are required. In [112], a method of diminishing marginal utility for optimal design of SWH is proposed, where the optimal size of the solar collector area and the storage tank volume are determined to be $194m^2$ and $89m^3$ for the case study system.

The study is based on a building site rather than a single house situation. For residential home systems, the benefits could be further improved if economic hybrid PV-thermal systems and additional ESS are considered.

3.6 Summary

In this chapter, the EV and V2G technologies relevant to the thesis work are introduced including optimal charging management of EV with and without V2G. Some doubts on use of V2G technology are presented. Furthermore, the fundamentals of solar thermal system are introduced. Some existing studies of load management for domestic water heating are reviewed.

Chapter 4 Minimisation of Household Energy Cost Considering ESS and EV with Driving Behaviour

EVs can be applied to reduce the (peak time) pressure on grid via the V2G technology. There is a constant debate on whether V2G is an economically viable option due to its high battery degradation cost. This question will be addressed, in this chapter, by considering whether customers could benefit from V2G programme under different FITs. Section 4.1 introduces the infrastructure of the residential home energy system. The power model is established in Section 4.2, where the EV driving behaviour is considered. The cost model including the key factors is described in Section 4.3. Case studies and results are discussed in Section 4.4. A summary is given in Section 4.5.

4.1 Residential home energy system

The residential loads in a typical home energy system are usually cannot be controlled, and the renewable generation is not included. In a smart home energy system, a PV generation is assumed to be installed. In order to adapt the variability and intermittency of PV generation, energy storage system (ESS) is very important to the smart home energy system, which can help the end user to storage the extra electricity power generated from PV and output power in an emergency situation or during the peak load period. Therefore, the infrastructure of the residential home energy system is illustrated in Fig. 4 - 1, where the components include a PV power system, an EV, an ESS, the lumped other residential loads, and the power grid. In Fig. 4 - 1, $P_1 > 0$ is the output power from the PV system, P_2 is the EV charging or discharging power, and P_3 is the input/output power of the ESS. Both P_2 and P_3 are variables to be controlled in the system. The remaining load of the residential home is represented by P_4 $(P_4 < 0)$. The smart home system is connected to the grid; the power to and from the grid is represented by P_5. The physical topological structure of the entire residential system is shown in Fig. 4 - 2.

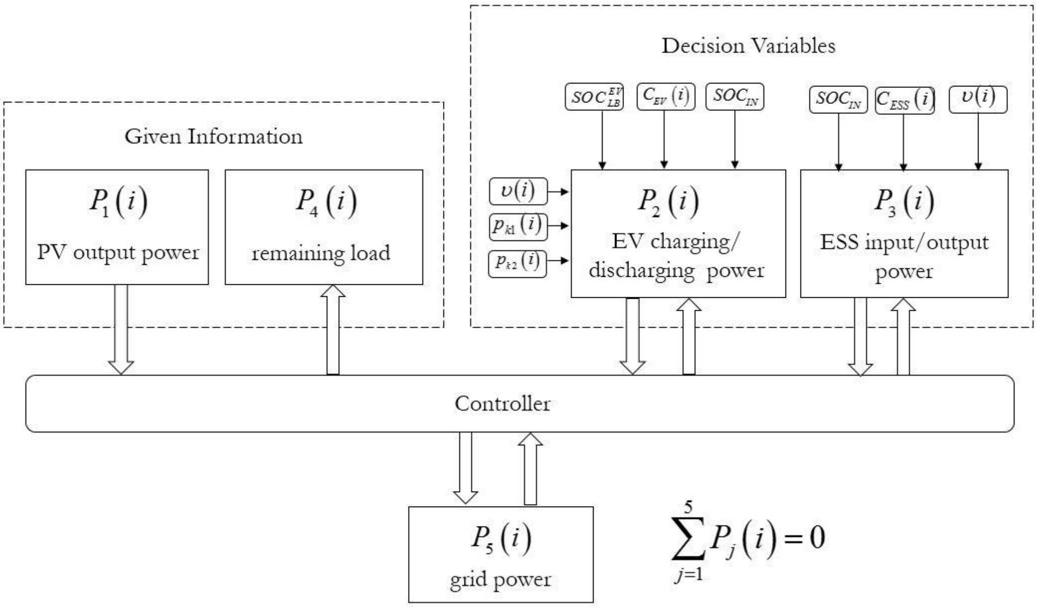

Fig. 4 - 1 Infrastructure of the residential home energy system

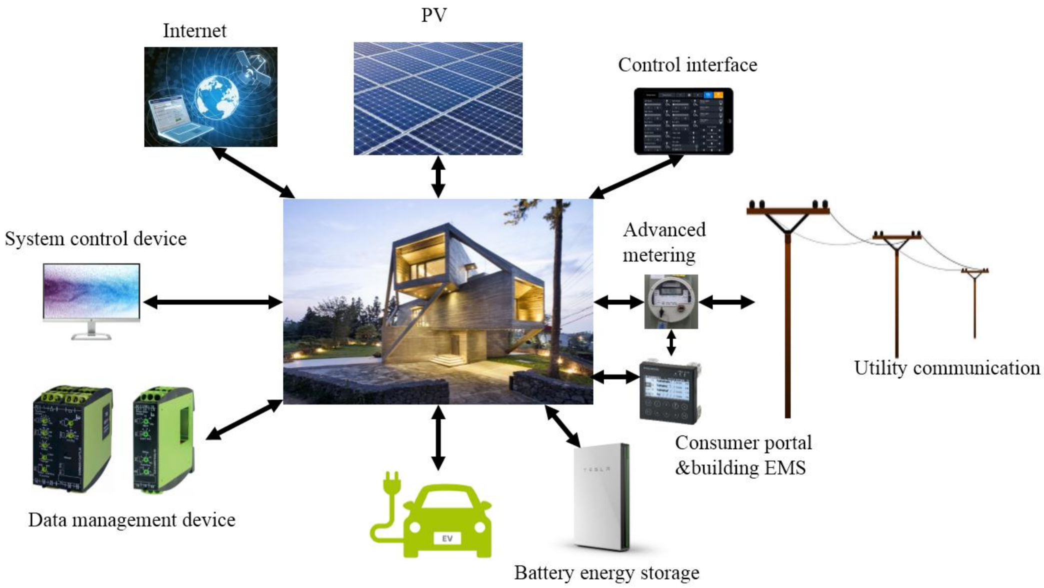

Fig. 4 - 2 Physical topological structure of the entire residential system

In Fig. 4 - 1, the arrows towards the optimisation (controller) block are defined as the positive direction indicating that the power P_j flows into the block. In this study, the total operational cost of the energy system is considered over a 24 hours' time period with the sampling period of 1 hour. In this case, there are 24 time periods or slots, each being denoted by index i ($i=1,2,\cdots,24$).The initial time period is assumed to start from 8:00 am where the time slot is set to be i=1. The units for all power flows are in kW. The basic relationship of the power flows can be described by the following power balance equation.

$$\sum_{j=1}^{5} P_j(i) = 0 \quad (i=1,2,\cdots,24) \tag{4.1}$$

It should be noted that $P_2(i)$ and $P_3(i)$ are the two variables that can be adjusted through optimisation, while $P_1(i)$ and $P_4(i)$ are fixed given information, and $P_5(i)$ can be calculated from (4.1) when the other four power factors are available.

4.2 Residential home system power model

4.2.1 Power for PV, ESS and EV with V2G

The PV power can be described by

$$P_1(i) = \lambda \cdot I(i) \cdot A \tag{4.2}$$

Here $I(i)$ is the solar irradiance ($\mathrm{kW/m^2}$); λ $(0<\lambda<1)$ is the solar irradiance to electricity conversion efficiency which is selected as 15% in this work; A is the solar panel area (m^2).

The charging/discharging power of EV and the power corresponding to on-off status of ESS can be described by the following expression.

$$\tilde{P}_2(i) = \begin{cases} +a\cdot\tau, & \text{if EV is discharing} \\ -a, & \text{if EV is charging} \\ 0, & \text{otherwise} \end{cases} \tag{4.3}$$

$$P_3(i) = \begin{cases} +a \cdot \tau, & \text{if ESS is discharing} \\ -a, & \text{if ESS is charging} \\ 0, & \text{otherwise} \end{cases} \tag{4.4}$$

a (kW) is a positive real number used for both EV and ESS; τ is the discharging efficiency accounting for the energy conversion loss, which is selected as 90% according to [113]. An intermediate term $\tilde{P}_2$ is used in (4.3) to refer to EV charging and discharging power without consideration of driving behaviours. In this work, the charging/ discharging powers for EV and ESS are assumed to be constant within each time slot. The levels of battery charging/discharging are considered to be the same for ESS and EV.

To simplify the model, when the vehicle is under the driving status, the discharging power is assumed to be constant and equal to the discharging power for V2G; therefore, variations of the power due to the change of driving behaviours such as acceleration or deceleration are ignored. That being said, the corresponding energy charged/discharged can be determined by the averaged charging/discharging effects.

4.2.2 Power model for EV considering driving behaviour

In order to characterise the uncertain nature of a car usage, a practical survey of vehicle daily usage is designed. The different driving purposes and usage in time are included in the survey. Information such as the driving distance for each drive, starting time and duration when the vehicle is away from home, time duration for parking outside, has been collected. Details of the survey and results are presented in Appendix. Then the raw data is processed and used to calculate the following probabilities:

$p_{k1}(i)$: the probability of EV parking and plugging in at home within time slot i ;

$p_{k2}(i)$: the probability that the EV is under driving within time slot i; and

$p_{k3}(i)$: the probability that the EV is parking outside within time slot *i.*

The sum of $p_{k1}(i)$ and $p_{k2}(i)$ is equal to 1, i.e.

$$p_{k1}(i) + p_{k2}(i) + p_{k3}(i) = 1 \tag{4.5}$$

In this study, these variations have been analysed from a real questionnaire (see Appendix A), in which the data has been transformed to the corresponding probabilities (see 4.3). Then, the mathematical expectation of the driving power consumption within each time slot is calculated.

The power flow from EV to the controller depends on whether the battery is under charging or discharging operation. Considering the driving probabilities, the EV power can be described as follows:

$$P_2(i) = \tilde{P}_2(i) \cdot p_{k1}(i) - Q_{EV} \cdot p_{k2}(i) \cdot \sum_{l=1}^{N_d} \frac{d(l)\, p_l}{d_{total}} \tag{4.6}$$

where d_{total} is the maximum distance (km) the EV can drive with a fully charged battery, Q_{EV} is the EV battery capacity (kWh). The total number of drives is represented by N_d, $d(l)$ is the *l*-th driving distance and p_l is the probability corresponding to $d(l)$ ($l = 1,\ldots,N_d$).When an EV is parking outside, it is assumed to be disconnected from the grid; therefore, no charging or discharging activities take place, and the term $p_{k3}(i)$ can be ignored for this situation. More details on EV driving behaviour can be seen in the survey results in Appendix.

As can be seen from (4.6), the second term is the mathematical expectation of driving power consumption. The daily use of a vehicle has many uncertainties for various reasons. When the EV's owner plugs out the vehicle from the charging slot leaving home, the remaining SOC of the EV will be different from when it is plugged back to the slot after the driving. The application of V2G technology will be influenced when considering these variations.

4.3 Calculations of vehicle driving/parking probabilities

The results of survey are shown in Appendix. A. According to the data in Table A. 1 and Table A. 3, the probability of EV being used outside of home for different purposes under certain time can be calculated. Therefore, the probability of EV being used outside,

$p_{k2}(i)+p_{k3}(i)$, for each sampling time can be obtained, and, $p_{k1}(i)$ can be calculated through (4.5), as shown in Table. 4 - 1.

Table. 4 - 1 Probabilities of EV usage (normalised in percentage for each column)

Time period	7:00-10:00	10:00-14:00	14:00-17:00	17:00-20:00	20:00-23:00	After 23:00
$p_{k2}(i)+p_{k3}(i)$	28.24	15.21	15.19	27.88	10.19	2.77
$p_{k1}(i)$	71.76	84.79	84.81	72.12	89.81	97.23

According to the Table A. 1 and Table A. 2, the driving distance $d(l)$ and the probability of different driving distance, p_l, can be obtained, which are shown in Table. 4 - 2.

Table. 4 - 2 Probability of different driving distance (normalised in percentage for each row)

$d(l)$, miles	< 1	1-3	3-5	5-10	10-20	20-40	40-80	80-120	120-160	160-200	200+
p_l	10.47	22.52	18.9	15.55	9.86	6.58	5.62	4.52	1.04	1.21	3.73

According to the data in Table A. 1, Table A. 4 and Table A. 5, the probability of driving time and outside parking time can be calculated, as shown in Table. 4 - 3and Table. 4 - 4, respectively. Assume that the inbound return driving time is the same as the outbound driving time for each trip, then it is calculated that the mean of the time that an EV is driving on road in a 24 hour period is around 140 minutes. The mean of the outside parking time can also be obtained, which is around 158 minutes. Therefore, when the EV is not plugged in at home, the probability of driving and parking outside can be approximately calculated, which are 46.94% and 53.06% respectively.

Table. 4 - 3 Probability of different driving time (normalised in percentage for each row)

Driving time duration (one way)	< 10 mins	10 -20 mins	20 -30 mins	30 mins-1 hr	1 -2 hrs	2 -3 hrs	4 hrs
Probability	12	25	19	18	9	5	12

Table. 4 - 4 Probabilities of different outside parking time (normalised in percentage)

Parking time duration	< 10 mins	10 -20 mins	20 -30 mins	30 mins -1 hr	1 -2 hrs	2 -3 hrs	3 -5 hrs	6 hrs
Probability	10	10	9	11	16	14	9	21

According to Table. 4 - 1, and the probability that the EV is driving on the road at time point i, both $p_{k2}(i)$, and $p_{k3}(i)$, can be obtained, which are shown in Table. 4 - 5.

Table. 4 - 5 Probability of EV being outside of home (normalised in percentage)

Time period	7:00-10:00	10:00-14:00	14:00-17:00	17:00-20:00	20:00-23:00	After 23:00
$p_{k2}(i)$	13.26	7.14	7.13	13.08	4.78	1.30
$p_{k3}(i)$	14.99	8.07	8.06	14.79	5.41	1.47

4.4 Residential home cost model

The purpose of design is to minimise the total operational cost of the energy system, over a 24 hours' time period, via charging and discharging scheduling, so that the user's profit is maximised. The cost function, C_{total}, consists of the following parts: the degradation costs of the EV battery (C_{EV}) and the ESS battery (C_{ESS}) due to charging and discharging, the EV battery cost caused by driving ($C_{EV-outside}$), the cost to purchase electricity from the grid ($C_{purchase}$), and also the income from selling electricity to the grid (C_{income}) that is deducted from the total cost.

$$C_{total} = C_{EV} + C_{ESS} + C_{EV-outside} + C_{purchase} - C_{income} \tag{4.7}$$

4.4.1 EV and ESS battery degradation cost model

According to [114], a battery degradation consists of three parts: temperature related degradation, SOC related degradation, and the DOD related degradation. The temperature related degradation is caused by the fluctuations in charging power or discharging power. It is negligible for the EV parking at home and for the ESS since their charging/discharging current and voltage are usually stable. Therefore, only the SOC and DOD related degradation are considered in the following.

- **SOC-related degradation cost**

For both EV and ESS, the hourly cost of SOC - related degradation can be represented as follows [114]:

$$C_{SOC}(i) = C_0 \cdot \frac{\alpha \cdot SOC(i) - \beta}{CF_{max} \cdot y \cdot 365 \cdot 24}, \tag{4.8}$$

where C_0 is the battery purchase price, $SOC(i)$ is the value of SOC within time slot i. The two parameters, α and β, are determined by linear regression from the measured data, which are calculated to be $1.59 \cdot 10^{-5}$ and $6.41 \cdot 10^{-6}$, respectively [115]; CF_{max} is the maximum capacity fade constant which is assumed to be 20% after y years of battery use [115].

The relationship between charging /discharging power P and the SOC can be determined as $SOC = SOC_{IN} - P/Q$ [116], where SOC_{IN} is the initial value for the SOC, Q is the battery capacity. Since the driving probabilities will be considered, the EV's SOC can be derived from [116] as:

$$SOC_{EV}(i) = SOC_{IN}^{EV} - \frac{1}{Q_{EV}} \sum_{\rho=1}^{i} P_2(\rho) \tag{4.9}$$

From (4.8) and (4.9), the SOC - related degradation daily cost of the EV parking at home within the i-th time period is represented as follows:

$$C_{SOC}^{EV}(i) = \frac{C_0^{EV}}{CF_{max} \cdot y \cdot 365 \cdot 24} \left(\alpha \cdot \left(SOC_{IN}^{EV} - \frac{1}{Q_{EV}} \sum_{\rho=1}^{i} P_2(\rho) \right) - \beta \right) \tag{4.10}$$

- **DOD-related degradation cost**

The DOD - related degradation cost per discharging cycle (£/cycle) can be expressed by $C_0 \cdot \left(\frac{\Delta L_{DOD}}{N_{total}} \right)$ where N_{total} is the total number of discharging cycles corresponding to ΔL_{DOD} [114]. ΔL_{DOD} is the DOD of a particular discharging cycle, which can be obtained as $P_{\text{EV-Discharge}} / Q_{EV}$, where $P_{\text{EV-Discharge}}$ is the total discharging power for V2G during the day. It can be expressed as:

$$P_{\text{EV-Discharge}} = \sum_{i=1}^{24} P_2(i) \cdot \text{sgn}(P_2(i)) \cdot \tag{4.11}$$

and the sign function $\text{sgn}(\cdot)$ is defined as:

$$\text{sgn}(x) = \begin{cases} 1, & if \;\; x \geq 0; \\ 0, & otherwise. \end{cases} \tag{4.12}$$

The value of N_{total} is related to the DOD [117], as depicted in Fig. 4 - 3. In this study, the polynomial function between N_{total} and ΔL_{DOD} is obtained through curve fitting, as represented by (4.13).

$$N_{total} = f(\Delta L_{DOD}) = \\ \left(1.06 \cdot (\Delta L_{DOD})^4 - 2.80 \cdot (\Delta L_{DOD})^3 + 2.66 \cdot (\Delta L_{DOD})^2 - 1.07 \cdot (\Delta L_{DOD}) + 0.17 \right) \cdot 10^5 \tag{4.13}$$

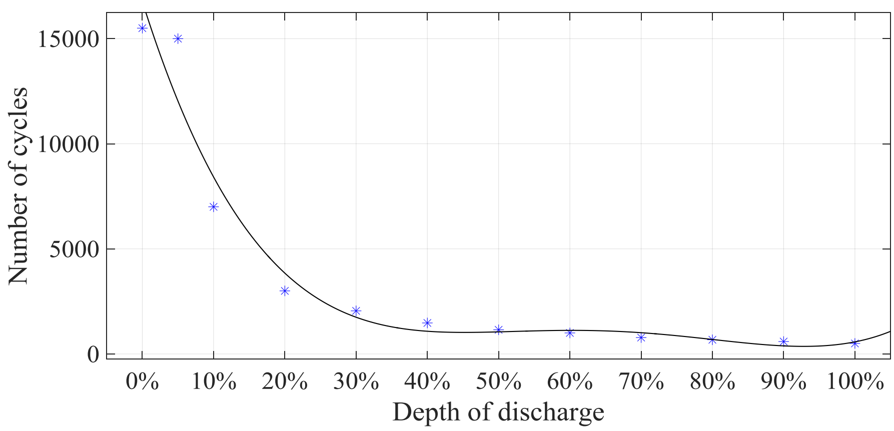

Fig. 4 - 3 Battery lifecycle number vs. DOD from manufacturer's data [117]

Hence, the DOD degradation cost per discharging cycle can be written as $C_0 \frac{\Delta L_{DOD}}{f\left(\Delta L_{DOD}\right)}$. Assume that there are n_1 discharging cycles during 24 hours, with each of them corresponding to a DOD degradation cost, then the DOD related degradation daily cost is represented as follows:

$$C_{DOD} = \sum_{m=1}^{n_1} \frac{\Delta L_{DOD,m}}{f\left(\Delta L_{DOD,m}\right)} C_0 \tag{4.14}$$

Following (4.14), the DOD related degradation cost of EV parking at home within time period i, denoted by $C_{DOD}^{EV}\left(i\right)$, can be written as:

$$C_{DOD}^{EV}\left(i\right) = \sum_{m=1}^{n_1} \frac{\Delta L_{DOD,m}(i)}{f\left(\Delta L_{DOD,m}(i)\right)} C_0^{EV} \cdot p_{k1}\left(i\right) \tag{4.15}$$

Similarly for the ESS, the SOC related degradation cost and the DOD related degradation cost within the *i*-th time period, denoted by $C_{SOC}^{ESS}\left(i\right)$ and $C_{DOD}^{ESS}\left(i\right)$, respectively, are written as follows:

$$C_{SOC}^{ESS}\left(i\right) = \frac{C_0^{ESS}}{CF_{max} \cdot y \cdot 365 \cdot 24} \left(\alpha \cdot \left(SOC_{IN}^{ESS} - \frac{1}{Q_{ESS}} \sum\nolimits_{\rho=1}^{i} P_3\left(\rho\right) \right) - \beta \right) \tag{4.16}$$

$$C_{DOD}^{ESS}\left(i\right) = \sum_{m=1}^{n_1} \frac{\Delta L_{DOD,m}(i)}{f\left(\Delta L_{DOD,m}\right)} C_0^{ESS} \tag{4.17}$$

where Q_{ESS} is the ESS battery capacity.

The overall battery degradation cost of EV and ESS over 24 hours is the sum of degradation cost from SOC and DOD for both EV and ESS at each hour, thus

$$C_{EV} + C_{ESS} = \sum_{i=1}^{24} \left(C_{SOC}^{EV}\left(i\right) + C_{DOD}^{EV}\left(i\right) + C_{SOC}^{ESS}\left(i\right) + C_{DOD}^{ESS}\left(i\right) \right) \tag{4.18}$$

4.4.2 EV cost due to driving

In this thesis, it has been assumed that EV has a 20% maximum capacity fade constant value which is represented by CF_{max}. The whole EV's battery lifetime is represented by y years; therefore, in order to calculate the degradation costs due to EV driving outside of home, we assume that the average daily battery degradation cost, $C_{EV-average}$, is the total daily degradation cost, which can be calculated by the following equation (4.19)

$$C_{EV-average} = C_0 \cdot \frac{CF_{max}}{y \cdot 365} \tag{4.19}$$

Considering the driving probabilities, $C_{EV-outside}$ can be calculated as follows

$$C_{EV-outside} = C_{EV-average} \cdot \left(1 - \prod_{i=1}^{24} \left(1 - p_{k2}(i)\right) \right) \tag{4.20}$$

where $1 - \left(\prod_{i=1}^{24} \left(1 - p_{k2}(i)\right) \right)$ is the probability of using vehicle outside home during the day.

4.4.3 Purchasing costs and selling incomes from/to grid

The total electricity purchasing cost, $C_{purchase}$, is determined by $P_5(i)$ only where $P_5 = -\sum_{j=1}^{4} P_j$, therefore

$$C_{purchase} = \sum_{i=1}^{24} P_5(i) \cdot \operatorname{sgn}\left(P_5(i)\right) \cdot \mu(i) \tag{4.21}$$

where $\mu(i)$ is the unit electricity price.

Here only the positive values of $P_5(i)$ are considered in the purchasing cost.

According to [118], the FIT value, consists of two parts: the generation tariff, $\upsilon_{\text{generation}}(i)$, and the export tariff, $\upsilon_{\text{export}}(i)$. The generation tariff is a fixed payment from the electricity supplier for every kWh of electricity the renewable system generates, such as PV in this work. The export tariff is the unit payment for every kWh of electricity the system exports back to the electricity supplier. Therefore, the income C_{income} from selling electricity to the grid is determined by the negative values of $P_5(i)$ and the total electricity generation from the PV system, and the daily income can be written as follows:

$$C_{income} = \sum_{i=1}^{24} P_5(i) \cdot \left(\operatorname{sgn}\left(P_5(i)\right) - 1 \right) \cdot \upsilon_{\text{export}}(i) + \sum_{i=1}^{24} P_1(i) \cdot \upsilon_{\text{generation}}(i) \tag{4.22}$$

4.4.4 Overall cost function and the optimisation problem

Taking (4.18), (4.21) and (4.22) into (4.7) will give the total cost over a daily period. The cost within each time period is a function of P_2 and P_3. The displayed SOC in an EV's panel is from 0% to 100%, which corresponds to the allowed driving distance ranging from 0 to the maximum, respectively. In this study, the following two constraints are considered for the displayed SOC.

$$SOC_{\min}^{EV} \le SOC_{EV-display}(i) \le SOC_{\max}^{EV} \tag{4.23}$$

$$SOC_{\min}^{ESS} \le SOC_{ESS-display}(i) \le SOC_{\max}^{ESS} \tag{4.24}$$

In addition, when the EV is plugged in to the slot at home, the SOC value at the end of the control period, i.e., at $i = 24$, needs to be larger than the SOC required for the next driving. This constraint is termed as the *minimal terminal SOC constraint* and is given as follows:

$$SOC_{EV-dispaly}(24) \ge \frac{d_{exp}}{d_{total}} \cdot 100 = SOC_{LB}^{EV} \tag{4.25}$$

where d_{exp} is the expected driving distance over the next driving period. It can be taken as the expected driving distance over the next day if the period is 24 hours. The ratio of

d_{exp}/d_{total} represents the required SOC for the next driving period, which is defined as the *lower bound of the terminal SOC*, denoted as SOC_{LB}^{EV} .

Taking all the above constraints into account, the following optimisation problem is formulated to minimise the total operating cost of the energy system.

$$\begin{aligned} &\min C_{total}\left(P_2, P_3\right) \\ &\text{subject to: } SOC_{\min}^{EV} \leq SOC_{EV}\left(i\right) \leq SOC_{\max}^{EV} \\ &\qquad SOC_{\min}^{ESS} \leq SOC_{ESS}\left(i\right) \leq SOC_{\max}^{ESS} \\ &\qquad SOC_{EV}\left(24\right) \geq SOC_{LB}^{EV} \\ &\qquad \sum_{j=1}^{5} P_j(i) = 0 \end{aligned} \tag{4.26}$$

In this work, the optimisation problem is to minimise the end user's energy cost, where the decision variables are the charging/discharging status of EV and ESS. Therefore, the optimisation problem is an integer programming problem. The GA algorithm has been applied to solve this problem. A flow diagram of the optimisation model has been shown in Fig. 4 - 4.

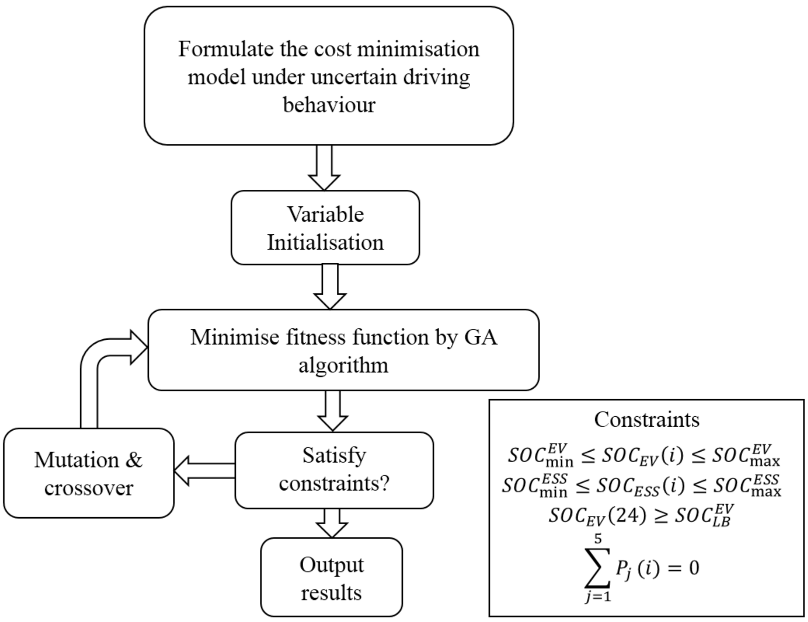

Fig. 4 - 4 A flow diagram of the optimisation model

4.5 Case studies: implementation, results and discussions

In this section, the optimal charging/discharging operations of EV and ESS for the residential home energy system are studied under different scenarios.

4.5.1 System specifications

Two types of tariff are considered and compared in the case study; namely, the fixed tariff and the time-of-use (TOU) tariff. The fixed tariff is £0.152 per kWh, sourced from the Energy Shell Company. The 2014 TOU tariff is taken from the Scottish and Southern Energy Public Limited Company [119]. The peak time period is from 17:00 to 20:00, and the corresponding tariff is £0.234/kWh. The night time period is from 01:00 to 07:00, and the corresponding tariff is £0.061/kWh. The rest of the day is regarded as the off-peak time period and the tariff is £0.117/kWh. The two tariffs are illustrated in Fig. 4 - 5.

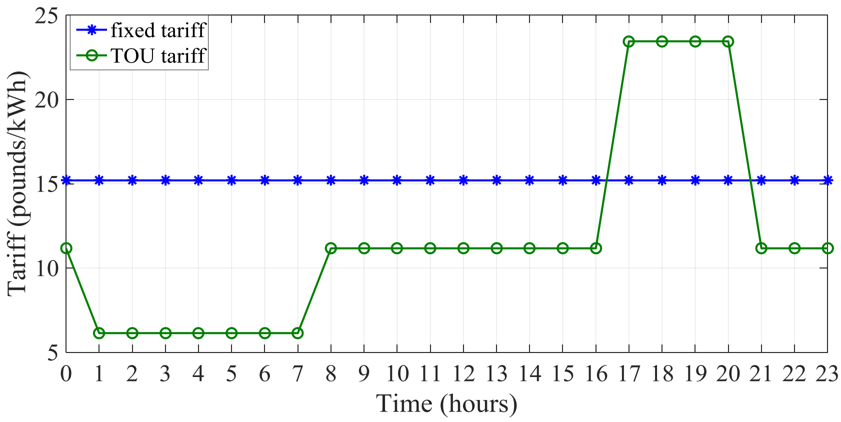

Fig. 4 - 5 Comparison of the fixed tariff and the TOU tariff

The solar PV rating is less than 10kW, and the solar panel area for PV generation is selected to be $16m^2$. Usually, the export tariff is regulated by the government, which is 5.03 pence/kWh in UK. In addition, if the PV system is less than 10 kW, the generation tariff is 3.93 pence/kWh up to now [118]. Each EV's battery price, shown in Table. 4 – 6, is estimated from the data in [120], which equals approximately 30% of the total projected price. The TESLA Powerwall is selected for the ESS battery storage. It has the capacity of 6.4kWh and the cost of $3,000 (approximately £ 2,300) per pack. Also, the ESS capacity can be expanded through the connection to multiple TESLA Powerwalls.

The grid voltage supply to the residential house is assumed to be 230V, and the charging/discharging current for EV and ESS are all 10A. In this chapter, the whole battery life of EV is assumed to be 15 years, so the average daily degradation costs, $C_{EV-average}$, due to driving can be obtained as shown in Table. 4 – 6.

Table. 4 – 6 Price of EV battery packs

Brand	TESLA	TESLA	BMW I3	SMART	LEAF
Capacity (kWh)	75	100	33	17.6	40
Projected EV Price (£)	64700	86200	34070	21465	21990
Evaluation Price of Battery(£)	19410	25860	10221	6440	6597
Unit Capacity Cost (£/kWh)	258.8	258.6	309.7	365.8	164.9
$C_{EV-average}$ (£)	0.70	0.94	0.37	0.23	0.24

The data for other residential loads such as lighting, cooking ,heating, washing/drying and heating, excluding EV and ESS, are sourced from [33], which is shown in Fig. 4 - 6. The solar raidation is selected from [109], which is the average hourly solar radition in January and it is shown in Fig. 4 - 7.

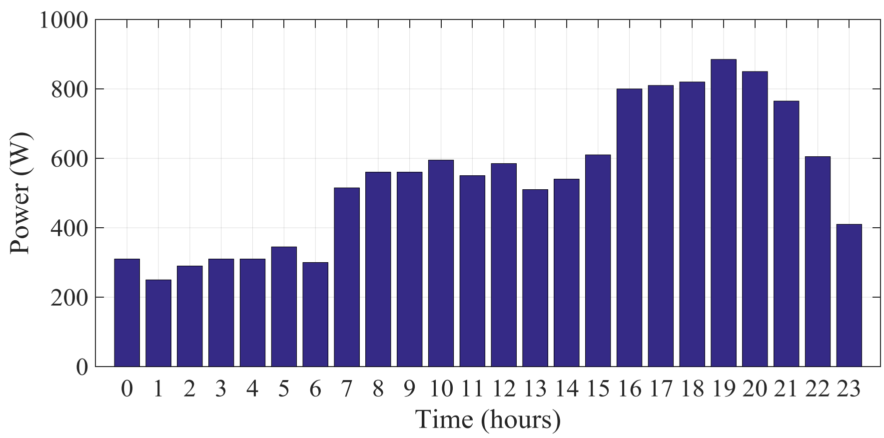

Fig. 4 - 6 Other residential loads during the selected day [33]

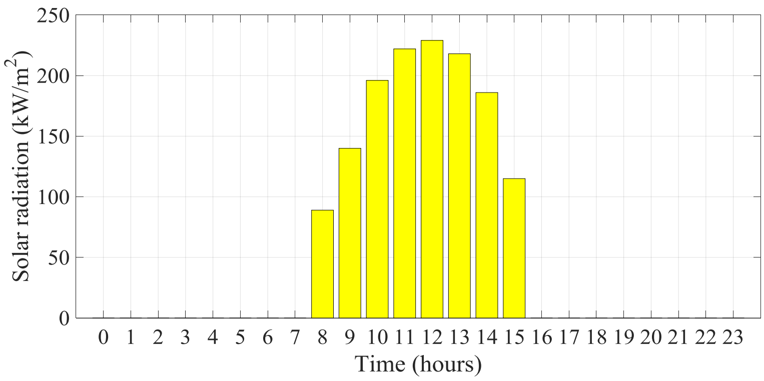

Fig. 4 - 7 Solar radiation in January [109]

4.5.2 Numerical studies under different terminal SOC constraints and initial SOC of EV

In this case study, the initial values of the displayed SOC in the ESS is fixed as 0%. The selected EV model is BMW I3, for which the battery pack's price is approximately £10,221. The operational cost minimisation problem in (4.26) is solved under different values of SOC_{LB}^{EV}.

Both fixed tariff and TOU tariff are applied, and the minimal operation costs under different levels of SOC_{LB}^{EV} are shown in Fig. 4 - 8 for fixed tariff and Fig. 4 - 9 for TOU tariff, respectively. It can be seen that user's cost increases with the increase of SOC_{LB}^{EV} provided that $SOC_{LB}^{EV} > SOC_{IN}^{EV}$. This is because the EV needs to be charged in order to ensure a higher remaining SOC at the end of the control period. If $SOC_{LB}^{EV} < SOC_{IN}^{EV}$, then the user's minimal operational cost stays at the same minimum value as shown in Table. 4 - 7 and Table. 4 - 8, which means no charging or discharging takes place. The optimised results on $P_2(i)$ and $P_3(i)$ show that there is no discharging either from EV or from ESS when $SOC_{LB}^{EV} < SOC_{IN}^{EV}$, which means that there is no power sold back to the grid under this circumstances. This is because the value of the export tariff is too low, and the degradation cost of battery discharging cannot be compensated under such a low tariff. In addition, it can be observed that the operational cost under the given TOU tariff is lower than that of the fixed tariff.

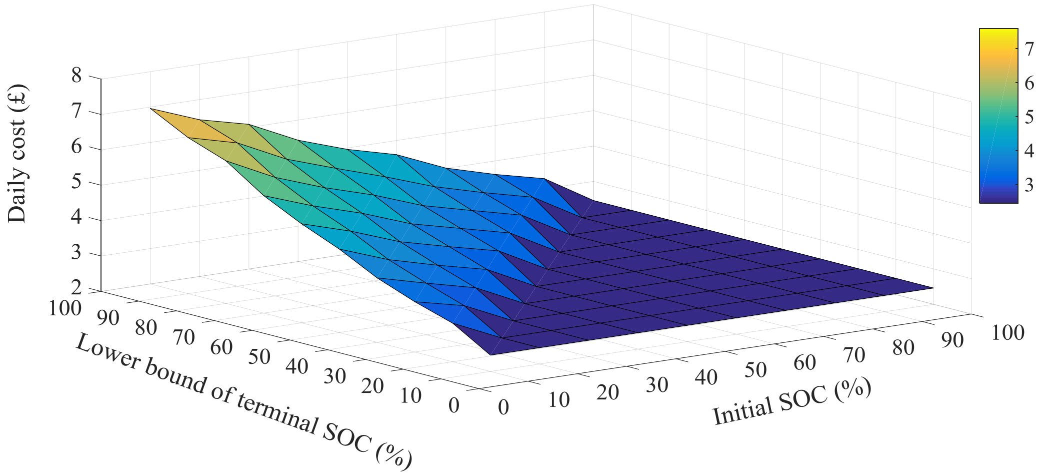

Fig. 4 - 8 Impact of different SOC constraints and initial SOC of EV under fixed tariff

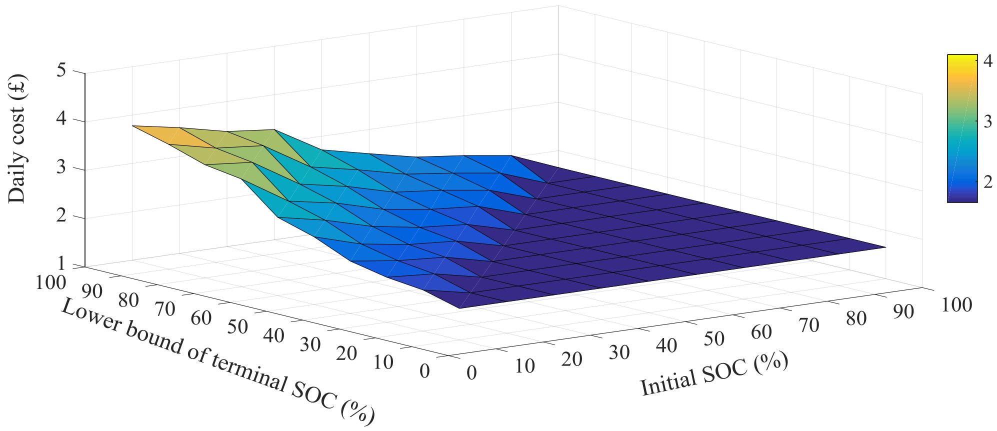

Fig. 4 - 9 Impact of different SOC constraints and initial SOC of EV under TOU tariff

The impact of the initial SOC of EV, SOC_{IN}^{EV}, to the minimal operational cost is studied next. Here SOC_{LB}^{EV} is fixed at 50%. SOC_{IN}^{EV} is assumed to take a set of values between 0 to 100%, and all other system parameters are kept the same as in Section 4.5.2. The results are also shown in Fig. 4 - 8 and Fig. 4 - 9.

It can be observed that the operational cost to charge the same amount of energy to the battery will increase when the initial SOC increases. For example, according to the results of the fixed tariff in two scenarios shown in Table. 4 - 7 and Table. 4 - 9, the optimal operational cost is £4.68 to charge the EV from $SOC_{IN}^{EV} = 0$ to $SOC_{EV} = 50\%$; however, it can be seen from Table. 4 – 9 that a slightly higher cost of £4.73 is needed to charge the EV from $SOC_{IN}^{EV} = 50\%$ to $SOC_{EV} = 100\%$, although in both cases, charging of the battery requires the same amount of energy. The underlying reason can be understood from (4.8), where it shows that a lower initial SOC will lead to a lower battery degradation cost. For the TOU tariff, the results give a similar conclusion that the operational cost decreases with the increase of the initial SOC.

Table. 4 - 7 Minimal operational cost under the fixed tariff and different SOC_{LB}^{EV}

SOC_{LB}^{EV} (%)	Cost (£)	SOC_{LB}^{EV} (%)	Cost (£)
0	2.23	60	2.76
10	2.23	70	3.34
20	2.23	80	3.74
30	2.23	90	4.37
40	2.23	100	4.73
50	2.23		

Table. 4 - 8 Minimal operational cost under the TOU tariff and different SOC_{LB}^{EV}

SOC_{LB}^{EV} (%)	Cost (£)	SOC_{LB}^{EV} (%)	Cost (£)
0	1.65	60	1.91
10	1.65	70	2.24
20	1.65	80	2.6
30	1.65	90	2.96
40	1.65	100	3.33
50	1.65		

Table. 4 - 9 Daily operational cost under different initial SOC with the fixed tariff

Initial SOC (%)	Cost (£)	Initial SOC (%)	Cost (£)
0	4.68	60	2.23
10	4.25	70	2.23
20	3.66	80	2.23
30	3.32	90	2.23
40	2.69	100	2.23
50	2.23		

Table. 4 - 10 Daily operational cost under different initial SOC with the TOU tariff

Initial SOC (%)	Cost (£)	Initial SOC (%)	Cost (£)
0	3.24	60	1.65
10	2.86	70	1.65
20	2.47	80	1.65
30	2.17	90	1.65
40	1.9	100	1.65
50	1.65		

4.5.3 Impacts of different EV models

In this section, the influence of EV models is examined. The tariffs and the specifications for the PV and the ESS are the same as in the previous discussions. The initial value of SOC is set to be 50% for all EV models, and 0% for the ESS. In order to keep the minimum cost and the maximum residual SOC for EV, the lower bound of the terminal SOC for EVs is selected to be the same as the initial SOC, i.e., $SOC_{LB}^{EV} = SOC_{IN}^{EV} = 50\%$.

With the fixed tariff of £0.152/kWh, Table. 4 - 11 shows the daily minimal operational cost under different choices of EV models. From the customer's cost perspective, the most economic EV model is the 17.6kWh SMART, which has the minimal daily operational cost of £2.23 and its purchase cost of the battery pack is £6,440. There are two reasons that can explain why SMART can achieves the lowest daily cost. Firstly, according to (4.8), if the battery purchase cost is higher, the degradation cost will be higher. However, this does not imply that the minimal operational cost of an EV with higher battery capacity will always be larger than that with lower battery capacity. Another important factor is the driving efficiency of EV. In Table. 4 - 11, the driving efficiency is shown in the third column, and it is evaluated by the driving distance per kWh denoted by u_m. It can be observed that a higher value of u_m provides a lower daily operational cost. Therefore, the daily cost depends on both of the EV battery price and the driving efficiency.

Table. 4 - 11 Daily cost for different types of EV models under fixed tariff

EV models	Operational cost (£)	Unit driving distance u_m (miles/kWh)
BMW I3	2.23	4.28
SMART	2.17	5.63
LEAF	2.21	4.20
TESLA (75)	2.64	4.05
TESLA (100)	2.71	3.93

Next, the TOU tariff is employed to check the impacts of EV models, and Table. 4 - 12 shows the resulting daily minimal operational cost under different battery capacities. It can be observed again that the 17.6kWh SMART is again the most economic one.

Table. 4 - 12 Daily cost for different EV models under TOU tariff

EV models	Operational cost (£)
BMW I3	1.65
SMART	1.58
LEAF	1.61
TESLA (75)	2.02
TESLA (100)	2.10

Fig. 4 - 10 illustrates the operational cost comparison between the fixed and the TOU tariffs. It can be seen that the 17.6kWh SMART has the lowest operational cost under both tariffs, and the given TOU tariff is much more economical compared to the given fixed tariff.

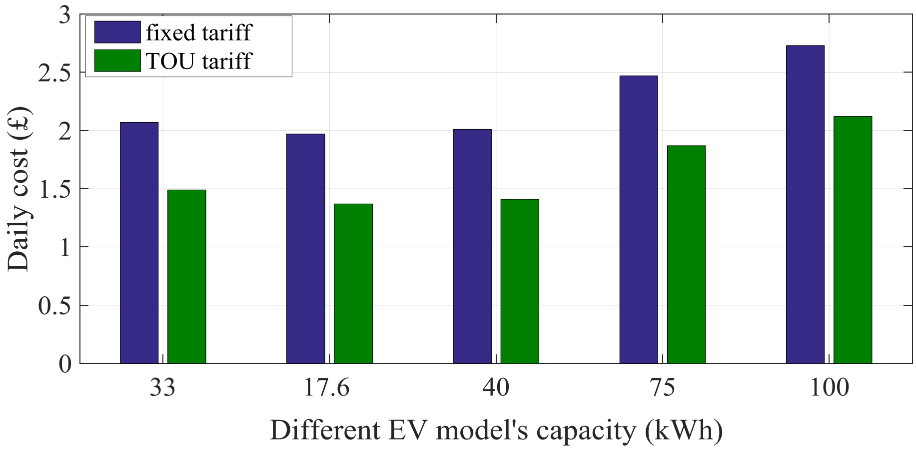

Fig. 4 - 10 Daily operational cost under different battery capacities

4.5.4 Impacts of different $\upsilon_{\text{export}}(i)$ of FITs

The υ_{export} value of FIT will affect end users whether to participate in V2G market or not. In the following simulation, the initial SOC values are set to be 100% for both EV and ESS (fully charged). The lower bound of terminal SOC is selected as 0% so as to check the maximum possible amount of energy discharged and obtain the minimum value of υ_{export} which allows V2G profitable. After comparing different EV charging/discharging results from the optimisation, it is found that EV will start to discharge power only if the export tariff is larger than the threshold value of £0.25/kWh for the fixed tariff, and £0.15/kWh for the TOU tariff. The simulation result shows that the export tariff has to be at least £0.96/kWh in order to achieve a positive net income under a fixed tariff, and £0.60/kWh under a TOU tariff. These results are shown in Table. 4 - 13 and Table. 4 – 14 for the fixed and the TOU tariffs, where a negative value of operational cost implies there is a positive net income. Fig. 4 - 11 and Fig. 4 - 12 show the results of EV and ESS charging/discharging status for the TOU tariff, where '+1' means discharging, '-1' means charging, and '0' means no charging or discharging taking place.

It can be found from Fig. 4 - 11 that the EV discharging time is within the electricity consumption peak time period. This can help to shave the peak load for the end user, so it can be concluded that the charging/discharging profiles of EV and ESS are influenced by the electricity tariff. In addition, the charging/discharging profiles of EV is also influenced by the probability of EV parking at home. According to the survey data, the probability of EV parking at home during night time is much higher than during the day time; therefore, the EV charging/discharging can be operated more often during the night time.

Compared with EV, such a parking-at-home probability factor is not applicable to ESS, so the electricity tariff is the only factor that influences the scheduling of ESS charging/discharging. When the electricity tariff is fixed, there are in general many random solutions for ESS satisfying all the constraints, including the SOC constraints. Therefore it is of less interest to discuss the fixed tariff situation. As can be seen from Fig. 4 - 12, ESS is charged during the off-peak time when the tariff is the lowest, and discharged during the peak-time when the tariff is the highest. This verifies that the results calculated through the model are reasonable for practical applications, and the optimisation solution is more efficient under the TOU tariff than that under the fixed tariff. The results of minimal with respect to υ_{export} is compared for fixed and TOU tariffs in Fig. 4 - 13. It shows that the TOU tariff provides more benefit for the user.

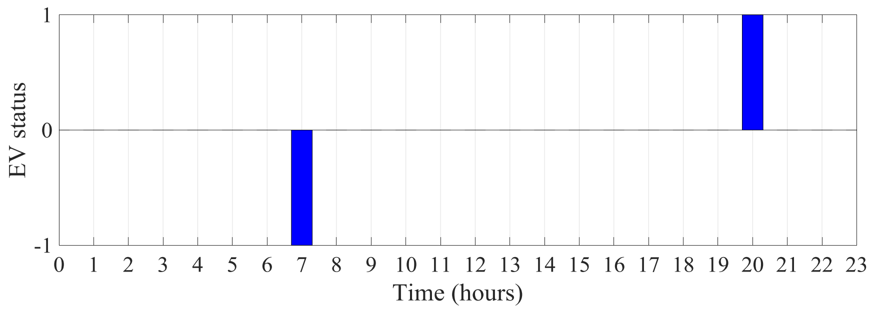

Fig. 4 - 11 EV charging/discharging profile under TOU tariff

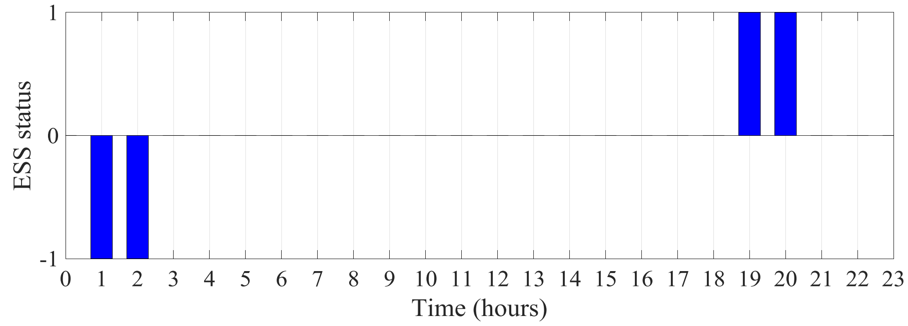

Fig. 4 - 12 ESS charging/discharging profile under TOU tariff

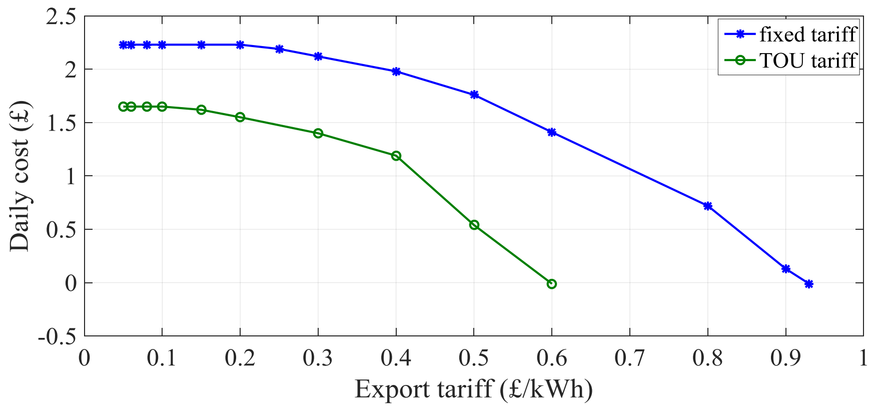

Fig. 4 - 13 Impact of export tariff to daily minimal operational cost

Table. 4 - 13 Daily minimal operational cost under fixed tariff

FIT (£)	Cost (£)	FIT (£)	Cost (£)
0.05	2.23	0.3	2.12
0.06	2.23	0.4	1.98
0.08	2.23	0.5	1.76
0.1	2.23	0.6	1.41
0.15	2.23	0.8	0.72
0.2	2.23	0.9	0.13
0.25	2.19	0.93	-0.01

Table. 4 - 14 Daily minimal operational cost under TOU tariff

FIT (£)	Cost (£)	FIT (£)	Cost (£)
0.05	1.65	0.2	1.55
0.06	1.65	0.3	1.4
0.08	1.65	0.4	1.19
0.1	1.65	0.5	0.54
0.15	1.62	0.6	-0.01

4.5.5 Impacts of different probabilities of EV plugging in at home

In this case, the initial SOC value is set at 50% and the lower bound of the terminal SOC is 60%. Therefore, no matter how the other factors are varied, such as load change characteristics, PV generation characteristics and so on, the EV must be charged at least 10% (60%-50%) in order to satisfy the constraint. To investigate the impacts of different probabilities of EV parking at home, three sets of values are applied, 50%, 80%, and the probability value calculated from the survey. The electricity tariff is selected as TOU, which is shown in Fig. 4 - 5.

Results of EV charging status and daily cost for different probabilities are shown in Fig. 4 - 14, Fig. 4 - 15, Fig. 4 - 16 and Table. 4 - 15. It can be seen from these results that EV is only charged during night time period with the TOU tariff regardless of the parking probabilities. This is because the night time tariff is the lowest during the 24 hours period (1:00am to 7am). In addition, the results show that with the lower parking probabilities at home, it requires more times for charging the same amount of power, and this will lead to higher cost for the end user.

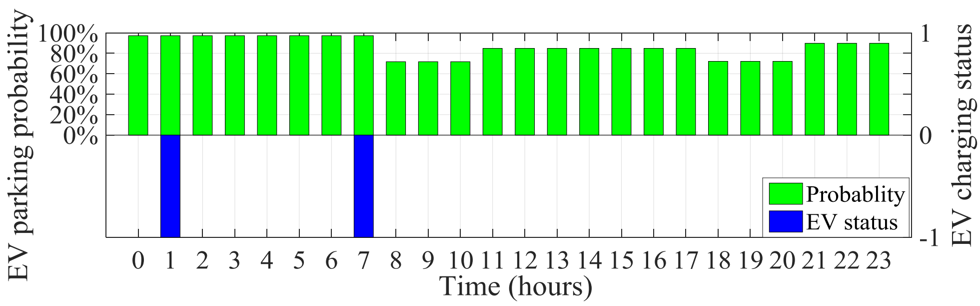

Fig. 4 - 14 EV charging/discharging profile under plugging-in probabilities of survey

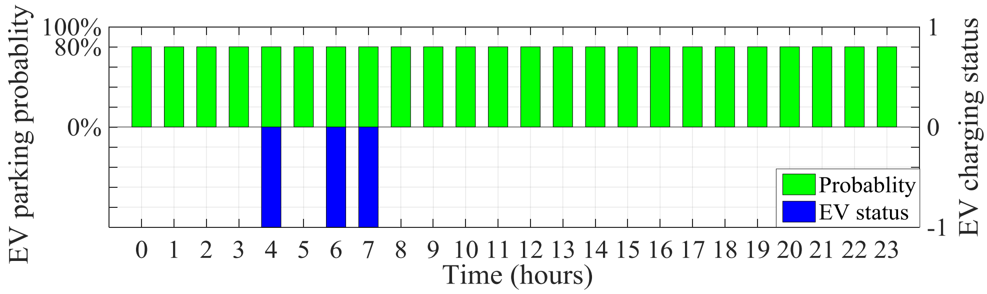

Fig. 4 - 15 EV charging/discharging profile if plugging-in probabilities is 80%

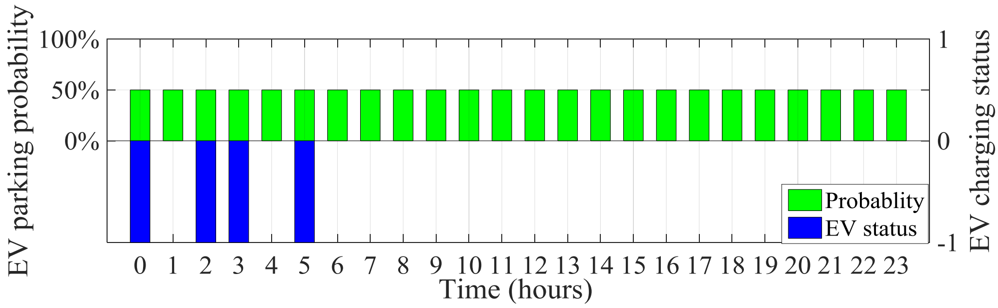

Fig. 4 - 16 EV charging/discharging profile if plugging-in probabilities is 50%

Table. 4 - 15 Daily cost of different plugging-in probabilities

Probability of plugging-in	EV charging times	Total cost (£)
50%	4	1.92
80%	3	1.84
Survey result	2	1.78

4.5.6 Battery degradation cost distribution due to active V2G

For the EV driving on the road, the expected value of the driving distance can be calculated from mathematical expectation formula, which is 28.7 miles according to the survey data in Table A. 1and Table A. 2. In addition, the probabilities of EV driving on the road within each time slot, $p_{k2}(i)$, are shown in Table. 4 - 5. Taking the BMW i3 as an example, if the EV is fully charged, the total driving distance is 188 miles according to the manufacture's report, so the expectation value of EV driving discharge, $\mathrm{E}\{DOD_{driving}\}$ can be obtained through $p_{k2}(i)$ *28.7/188, as shown in Table. 4 - 16. In this study, the output power for V2G service is assumed to be fixed at 2.3kW, so the DOD due to V2G for BMW i3 will be 7.0% for each sampling time, i.e., 2.3/33. The probability of EV parking and plug in at home at time point i, $p_{k1}(i)$, are shown in

Table. 4 - 1, from which the expectation value of EV discharged at home (V2G), $\mathrm{E}\{DOD_{V2G}\}$ at time point i can be obtained and listed in the following table.

Table. 4 - 16 Battery degradation cost due to V2G if it happens

Time Period	7:00 - 10:00	10:00 – 14:00	14:00 - 17:00	17:00 - 20:00	20:00 – 23:00	After 23:00
$\mathrm{E}\{DOD_{driving}\}$	2.02%	1.08%	1.08%	1.99%	0.72%	0.20%
$\mathrm{E}\{DOD_{V2G}\}$	5.02%	5.94%	5.94%	5.05%	6.29%	6.81%
Degradation cost percent due to V2G	71.31%	84.62%	84.62%	71.73%	89.73%	97.15%

4.5.7 Comparison between the cases with and without considering battery degradation cost

Here we consider the scenario when the battery degradation cost is ignored in the operational cost minimisation, and compare it with the previous cases where the battery degradation cost is included. This comparison is made with a focus on the impact of different EV capacities under the TOU tariff. All the initial values are the same as those in subsection 4.5.1. The results are shown in Table. 4 - 17 and Fig. 4 - 17.

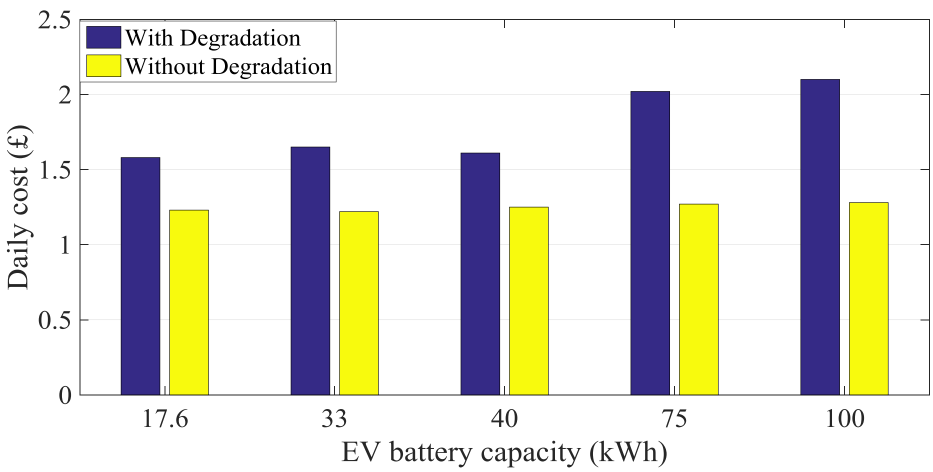

Fig. 4 - 17 Impact of battery degradation to daily minimal operational cost

Table. 4 - 17 Comparison of daily minimal operation cost

EV Models	Operational cost with battery degradation (£)	Operational cost without battery degradation (£)
BMW I3	1.65	1.23
SMART	1.58	1.22
LEAF	1.61	1.25
TESLA (75)	2.02	1.27
TESLA (100)	2.10	1.28

From Fig. 4 - 17, it can be observed that the daily cost of users is much lower when the battery degradation cost is ignored. However, this is not realistic because battery degradation always exists during charging and discharging processes. According to the results in Section 4.5.4, the given export tariff value cannot compensate the battery degradation cost for V2G service. It can be seen from results in Table. 4 - 16 that the V2G degradation costs occupy a large portion of the total battery degradation costs in all time periods; therefore, the optimisation without considering battery degradation cost is not feasible for the benefit of the end users.

4.5.8 Comparison of optimised strategy with baseline solutions

In this section, the user's daily cost under existing non-optimised operational schedule is compared with the optimised cost. ESS is not considered here as it is not popular in most of the non-optimised residential uses. The EV charging cost for driving, $C_{EV-driving}$, depends on how much the electricity power is charged to the battery, while the charging amount can be represented by the change of SOC. In addition, the expected charging amount of SOCs for different EVs in order to fulfil the tentative daily driving distance can be represented as $\sum_{l=1}^{N_d} d(l)\,p_l / d_{total}$; therefore, the daily driving costs can be expressed as:

$$C_{EV-driving} = \mu \cdot \sum_{l=1}^{N_d} \frac{d(l)\,p_l}{d_{total}} \tag{4.27}$$

where μ is the electricity price.

The battery degradation cost also needs to be added into the total cost. The average daily battery degradation costs for driving usage, $C_{EV-average}$, are calculated through (4.19). The overall non-optimised daily cost is calculated to through(4.28), which is also the baseline for cost reduction analysis.

$$
\begin{aligned}
C_{total}^{non-opt} = & \sum_{i=1}^{24} P_5(i) \cdot \left[\operatorname{sgn}\left(P_5(i)\right) \cdot \mu(i) - \left(\operatorname{sgn}\left(P_5(i)\right) - 1\right) \cdot \upsilon_{export}(i) \right] \\
& - \sum_{i=1}^{24} P_1(i) \cdot \upsilon_{generation}(i) + C_{EV-driving} + C_{EV-average}
\end{aligned}
\tag{4.28}
$$

Under the fixed tariff, the costs of selected EVs without optimisation are listed in Table. 4 - 18. The costs comparison with and without optimization are shown in Table. 4 - 19, from which it can be seen that the total daily cost without optimisation is much higher than the optimised cost. The highest cost saving is found to be 18% for TESLA (100) in under the fixed tariff.

Table. 4 - 18 Different EVs' daily charging cost without optimisation (fixed tariff)

EV	BMW I3	SMART	LEAF	TESLA(75)	TESLA(100)
Capacity(kWh)	33	17.6	40	75	100
$C_{EV-driving}$ (£)	0.77	0.85	0.98	0.98	1.03

Table. 4 - 19 Total daily cost comparison (fixed tariff)

EV Models	Total cost without optimisation (£)	Total cost after optimisation (£)	Cost reduction (%)
BMW I3	2.49	2.23	10%
SMART	2.43	2.17	11%
LEAF	2.56	2.21	14%
TESLA (75)	3.04	2.64	13%
TESLA (100)	3.32	2.71	18%

For TOU tariff, the daily charging costs for EVs without optimization are listed in Table. 4 - 20. The total daily cost saving is calculated to be 42% ~ 48% if the non-optimised charging time includes peak hours, and it is 18% ~ 19% if the non-optimised charging happens during night only, as shown in Table. 4 - 21. The obtained cost reduction in this work is higher than the case studies in [121], where the cost savings is up to 15.5%.

Table. 4 - 20 Different EVs' charging costs without optimisation (TOU tariff)

EV models	Peak time (£)	Off-peak time (£)	Night time (£)
BMW I3	1.18	0.59	0.32
SMART	1.31	0.65	0.36
LEAF	1.52	0.76	0.41
TESLA (75)	1.51	0.75	0.41
TESLA (100)	1.59	0.79	0.43

Table. 4 - 21 Total daily cost comparison (TOU tariff)

EV models	After optim. (£)	Non-optim. Peak time charging (£)	Cost reduct.	Non-optim. Off-peak time charging (£)	Cost reduct.	Non-optim. night time charging (£)	Cost reduct.
BMW I3	1.58	2.88	45%	2.23	29%	1.93	18%
SMART	1.65	2.87	42%	2.28	27%	2.01	18%
LEAF	1.61	3.10	48%	2.34	31%	1.99	19%
TESLA (75)	2.02	3.60	44%	2.84	29%	2.50	19%
TESLA (100)	2.10	3.75	44%	2.95	29%	2.59	19%

In addition, the total energy cost under the fixed tariff is higher than that under TOU tariff. It can be concluded that the EV owner is likely to have more benefit under the TOU tariff than that under the fixed tariff. The comparison on charging/discharging degradation cost impacts before and after optimisation are summarised in Table. 4 - 22.

Table. 4 - 22 Comparison of charging/discharging/degradation costs with and without optimisation

Cost impacts	With optimisation	Without optimisation
EV charging/discharging	● For fixed tariff, EV is charged when the parking probability is high, which will lead to lower cost. ● For a TOU tariff, EV is charged when the tariff is the lowest; and EV has higher probabilities of charging when the probabilities of parking at home is higher. ● V2G could happen with high FIT	● EV charging happens randomly throughout 24 hours no matter which tariffs are applied. ● NO V2G function even when FIT is high enough to compensate the degradation cost.
EV degradation	● Depends on the optimisation solution. For example, if more discharging happens with higher FIT, the degradation cost will be higher. However, the total cost will be reduced. If FIT is unchanged, the degradation cost will be similar to the value without optimisation.	● Mainly results from the amount of SOC charged/discharged and the daily driving distance.
ESS charging/discharging	● For fixed tariff, ESS will be charged/discharged randomly. ● For TOU tariff, ESS will be charged when the tariff is the lowest, and discharged when the tariff is high.	● EV charging happens randomly throughout 24 hours no matter which tariffs are applied. ● NO V2G

	• V2G could happen with high FIT.	
ESS degradation	• Similar to EV degradation	• Mainly results from the amount of SOC charged/discharged and the discharging time periods throughout a day.

4.6 Summary

In this chapter, an operational cost minimisation modelling framework is established for a residential energy system comprising of an EV, an ESS, a PV system, other residential loads, and the grid connection. To address the uncertain customer driving behaviours, the probabilities of different driving time periods are obtained through a set of survey data. The survey was developed to cover various factors including driving purposes, driving time periods and distance, and also EV parking time, etc.

The design objective is to minimise the overall cost of the residential energy system during a day through optimal scheduling of charging and discharging of EV and ESS.

Extensive simulation studies have been conducted. The impacts of the initial and the terminal SOC values are tested, where the results show that the total operational cost remains at the same minimum value if the initial SOC value is larger than or equal to the lower bound of the terminal SOC. This is because the existing υ_{export} is not large enough to compensate for the battery degradation cost, and thus, there is no power return either from ESS to home supply or from EV through V2G. Also, the overall cost measure will increase when the initial SOC is smaller than the lower bound of the terminal SOC. The overall cost for the end user will be slightly smaller if charging the same amount of energy to EV from a lower initial SOC.

Several EV models are considered, and the economical choice has been explored. Different impacts of υ_{export} of FIT are discussed. The results show that the EV will only start to discharge to grid when the υ_{export} is larger than or equal to £0.25/kWh for fixed tariff, and £0.15/kWh for TOU tariff in the case study. It can be concluded that V2G can only be profitable to end users when υ_{export} is larger than a certain threshold. This threshold could be decreased if the battery degradation cost can be reduced in the future.

Furthermore, a comparison is made with the non-optimised operation. It shows that the proposed optimisation can achieve cost savings from 9% to 15% under the selected fixed tariff, and from 18% to 48% under the given TOU tariff.

Chapter 5 Household Energy Cost Optimisation with Renewable Technologies: Solar Thermal and Photovoltaic Systems

In this chapter, the household energy optimisation has been extended to include solar energy supply. Solar energy has been regarded as one of the most abundant renewable sources. Photovoltaic (PV) systems transfer solar energy into electric form. PV-T is a hybrid system that converts solar radiation into electrical and thermal energy. For residential users with limited solar panel area, there are two options to achieve economic use of solar energy. One is to install both PV and solar water heater (SWH) systems, called PV-SWH, another one is to apply the PV-T system. Both options of PV-SWH and PV-T systems need to be discussed.

The modelling framework established in Chapter 4 has been expanded to include SWH systems. In addition to scheduling of EV and ESS charging/discharging, the switching on/off status of SWH is also controlled in DSM. The remaining part of this chapter is organised as follows. Section 5.1 introduces the two options of applying solar energy for water heating at residential homes. Section 5.2 presents the solar thermal model for water heating. The household energy system model that involves SWH is described in Section 5.3. Results and analysis from case studies are discussed in Section 5.4. Conclusions are given in Section 5.5.

5.1 Introduction to PV-SWH and PV-T systems

5.1.1 PV-SWH system

SWHs collect the solar radiation and transfer the energy for water heating. Details of SWH basics have been introduced in subsection 3.4. Because of the temperature of hot water should be within certain specified range for the ease of usage, too large area of SWH collectors is unnecessary at some high solar radiation area or during summer season. If the installation area for solar collector panels is limited for household users, combination of PV and SWH system can utilize the limited solar energy more efficiently to achieve economic energy savings for end user; so, this hybrid PV-SWH system is applied in this study.

5.1.2 PV-T system

PV-T is the system that convert solar radiation into electrical and thermal energy [122]. It combines both of solar cell and solar thermal collector, and converts solar radiation into electricity and captures the remaining energy for water heating usage. Therefore, PV-T collectors provide an efficient way to use solar energy and is more efficient than PV or solar thermal alone. The efficiency of PV cells will drop with the increase of the operating temperature of PV panels; however, water circulation in PV-T system can help to carry heat away from the PV cells, thereby cooling the cells and thus improving the electrical efficiency. Although PV-T system is an effective way to utilise the solar energy, the thermal component of this system will be under-performed compared to the solar thermal collector. Several studies have investigated the performance of PV-T system, and compared it to PV system or solar thermal system. In [123], a mathematical model of PV-T system is developed to calculate the system performance. The results show that the average thermal and electrical efficiency of the hybrid PV-T are 65% and 13.7%, respectively. In [124], it is concluded that there is a 2% increase in electrical efficiency of PV cells in PV-T system, and a 5% decrease in the thermal component of PV-T system compared to traditional SWH system. In [122], the electrical conversion efficiency of the PV-T system is improved about 10% compared to the PV system, and the maximum thermal efficiency of the system was found to be 51%.

Comparisons of PV-T with SWH or PV alone are seen in a few literature above, but the comparison of PV-T with combined SWH and PV is missing. In this work, the cost reductions between PV-T and PV-SWH will be investigated for residential users.

5.2 Solar thermal model for water heating

The collector, storage tank, loads and heat losses have been considered in this model [93]. To simplify the model, hot water in the storage tank is assumed fully mixed or non-stratified, and the storage tank is kept at a uniform temperature. Besides, the hot water outlet flow rate is assumed to be constant, the make-up water temperature is also constant, and the energy losses at the heat exchanger and pipes are ignored. The energy balance of the storage tank can be given as (5.1):

$$MC_p \frac{\mathrm{d}T_s}{\mathrm{d}t} = P_u(t) + P_e(t) - P_l(t) - P_{tl}(t) \tag{5.1}$$

where T_s is the temperature inside the tank; M is the mass of storage capacity (kg); C_p is the specific heat of water, which is 4,187$J/(kg \cdot ℃)$. The collected solar power delivered to the storage tank is represented by P_u and the power removed from the storage tank to load is P_l. P_{tl} is the power loss from storage tank, and P_e is the auxiliary electricity heat power. According to the energy system model in (4.26), there are 24 time periods or slots and each being denoted by index i ($i = 1, 2, \cdots, 24$), and the sampling time is 1 hour; therefore, (5.1) can be rewritten in discrete form as :

$$MC_p\left(T_s(i+1) - T_s(i)\right) = P_u(i) + P_e(i) - P_l(i) - P_{tl}(i) \tag{5.2}$$

The collected solar power delivered to the storage tank can be given by [125]:

$$P_u(i) = A_C F_R\left(S(i) - U_L\left(T_s(i) - T_a(i)\right)\right) \tag{5.3}$$

where A_C is solar collect area (m^2), $S(i)$ is absorbed radiation at time point i, F_R is the heat removal factor, which is 0.88 in this study and sourced from [126], and U_L is the product of the overall heat loss coefficient which is selected as $6.6\mathrm{W}/(\mathrm{m}^2 \cdot ℃)$ [125]. The storage tank hot water's temperature at time i is represented by $T_s(i)$, and $T_a(i)$ is the ambient temperature where the storage tank is located.

The absorbed radiation can be expressed as [125],:

$$S(i) = (\tau\alpha) I(i) \tag{5.4}$$

where $I(i)$ is solar irradiance, and $\tau\alpha$ is transmittance absorbance product which is selected as 0.86 [127].

The power removed from the storage tank to load can be written as:

$$P_l(i) = (\dot{m}C_p)\cdot\Delta t\cdot(T_s(i) - T_{mu}(i)) \tag{5.5}$$

where $\dot{m}$ is the mass flow rate (kg/hour), $T_{mu}(i)$ is the make-up water temperature, Δt is equal to the sampling time 1 hour. The storage tank power loss is given by [125]

$$P_{tl}(i) = (UA)(T_s(i) - T_a(i)) \tag{5.6}$$

where U is the storage tank loss coefficient and A is the tank area, their product (UA) is $2.8\ \text{W/}^\circ\text{C}$ on operation status and $1.9\ \text{W/}^\circ\text{C}$ on stand-by status [128].

From (5.3) to (5.6), the temperature inside the tank, in (5.2), can be rewritten as

$$\begin{aligned} T_s(i+1) = T_s(i) + \frac{1}{MC_p}\Big[& A_C F_R\big((\tau\alpha)I(i) - U_L(T_s(i) - T_a(i))\big) \\ & + P_e(i) - (\dot{m}C_p)\cdot\Delta t\cdot(T_s(i) - T_{mu}(i)) - (UA)(T_s(i) - T_a(i))\Big] \end{aligned} \tag{5.7}$$

5.3 Household energy system model involving SWH

The expanded smart home system is similar to the residential home system in Chapter 4. Again, the arrows towards the controller are defined as the positive direction which is the same as the home energy system in Chapter 4. The smart home energy system involving SWH is shown in Fig. 5 - 1.

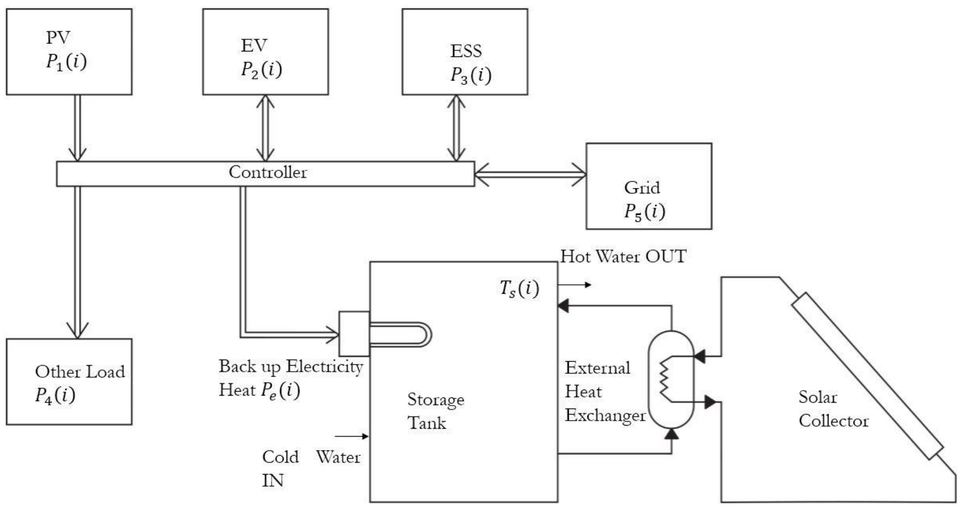

Fig. 5 - 1 Smart home energy system involving SWH

In Fig. 5 - 1, $P_1 > 0$ is the output power of the PV system, P_2 is the EV charging or discharging power, and P_3 is the input/output power of the ESS. P_e is the power of the back-up electric element in the SWH. P_2, P_3 and P_e are decision variables to be controlled in the optimisation design. The remaining load of the residential home is represented by P_4 $(P_4 < 0)$. The smart home system is connected to the grid and the input and output power to and from the grid is represented by P_5. The operation time period of the home system is considered as 24 hours with the sampling period of 1 hour; therefore, there are 24 time periods or slots, each being denoted by index i $(i = 1, 2, \cdots, 24)$. The initial time period is assumed to start from 8:00 am which corresponds to $i = 1$. The power balance equation of the smart home system can be described as in (5.8).

$$\sum_{j=1}^{5} P_j(i) + P_e(i) = 0 \qquad (i = 1, 2, \cdots, 24) \tag{5.8}$$

It should be noted that P_2, P_3 and P_e are the three variables that can be controlled through the model. The expressions of P_2 and P_3 have been formulated in Chapter 5, which are shown in (4.3), (4.4) and (4.6). The back-up electric element's power, P_e, is expressed as follows.

$$P_e(i) = \begin{cases} -\kappa, & \text{if water heated by SWH} \\ 0, & \text{otherwise} \end{cases} \tag{5.9}$$

The purpose of design is also to minimise the total operational cost of the energy system over a 24 hours' time period; therefore, the end user's profits can be maximised. The cost function, C_{total}, consists of the following parts, which is the same as (4.7): the cost to purchase electricity from the grid ($C_{purchase}$), the degradation cost of the EV battery (C_{EV}), the degradation cost of the ESS battery (C_{ESS}), the EV battery cost caused by driving ($C_{EV-outside}$), and also the income from selling electricity to the grid (C_{income}). In this chapter, the battery degradation cost models of EV and ESS are the same as Chapter 4. The electricity purchasing cost and the income from selling electricity to the grid are also the same as in Chapter 4, which are shown in (4.21) and (4.22). The values of $P_5(i)$ is calculated by $P_5 = -(\sum_{j=1}^{4} P_j + P_e)$. The total cost over the control period, C_{total}, while considering the variable P_e, can be expressed as:

$$\begin{aligned} C_{total} = C_{EV} + C_{ESS} + C_{EV-outside} + \sum_{i=1}^{24} \Big[& P_5(i) \cdot \operatorname{sgn}(P_5(i)) \cdot \mu(i) \\ & -\tau \cdot P_5(i) \cdot (\operatorname{sgn}(P_5(i)) - 1) \cdot \upsilon_{FIT}(i) \Big] \end{aligned} \tag{5.10}$$

The cost within each time period is a function of P_2, P_3 and P_e. The displayed SOC in an EV's panel is from 0% to 100%, which corresponds to the allowed driving distance ranging from 0 to the maximum, respectively. The two constraints for the displayed SOC of EV and ESS are considered as shown in (4.23) and (4.24). To ensure that the EV has enough power for next driving period, the minimal terminal SOC constraint should be given as well, which is the same as in (4.25). Furthermore, the comfort hot water temperature for human is around $40^\circ\mathrm{C}$. The hot water outlet temperature of the cylinder is usually set to be $50 \sim 65^\circ\mathrm{C}$, then use cold water to mix to around $40^\circ\mathrm{C}$ during shower. The hot water temperature in the storage tank should be confined in a certain range in order to satisfy the hot water demand throughout the day [116]. The following constraint is applied.

$$\left|T_s(i) - T_{expected}(i)\right| \leq Z \tag{5.11}$$

where Z is the permissible error range of the temperature; $T_{expected}(i)$ is the expected hot water's temperature at time period i. Taking all the above factors into account, the following optimisation problem is formulated to minimise the the total operating cost of for the smart home energy system.

$$\begin{aligned}
&\min C_{total}(P_2, P_3, P_e) \\
&\text{subject to: } SOC_{\min}^{EV} \leq SOC_{EV}(i) \leq SOC_{\max}^{EV} \\
&\qquad SOC_{\min}^{ESS} \leq SOC_{ESS}(i) \leq SOC_{\max}^{ESS} \\
&\qquad SOC_{EV}(24) \geq SOC_{LB}^{EV} \\
&\qquad \sum_{j=1}^{5} P_j(i) + P_e(i) = 0 \\
&\qquad \left|T_s(i) - T_{expected}(i)\right| \leq Z
\end{aligned} \tag{5.12}$$

As can be seen from (4.3), (4.4) and (5.9), the decision variables can be considered as the 0/1 or (0,1,-1), which makes an integer programming problem and the same with Chapter 4. However, the model built in Chapter 5 is non-linear optimisation problem. According to the literature review in Chapter 2, GA has the ability to deal with complex problems, and it can deal with various types of optimisation problems whether the objective functions are linear or non-linear, integer or real. Matlab has a built-in function for GA, which is applicable to mixed integer nonlinear programming problems. Thereofore, the GA algorithm has been applied again to solve the optimisation problem through MATLAB tool box. A flow diagram of the optimisation model included SWH has been shown in Fig. 5 -2.

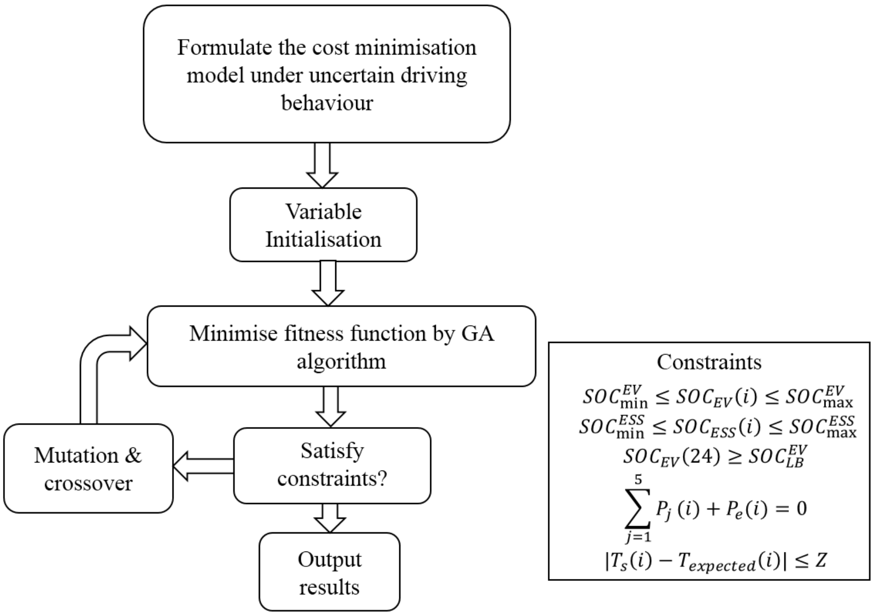

Fig. 5 - 2 A flow diagram of the optimisation model including SWH

5.4 Case studies: implementation, results and discussion

In this section, the smart home system, which is depicted in Fig. 5 - 1, will be studied in the optimisation framework for different scenarios. The relevant input data, such as daily load curve, hot water demand, and solar radiation and so on are collected from 5.4.1.

5.4.1 System specifications

Same as in Chapter 4, two types of tariffs are considered in the following case studies, the fixed tariff and time-of-use (TOU) tariff. Both of these tariffs are sourced from the same references in subsection 4.5.1, as shown in Fig. 4 - 5.

The solar PV's generation tariff and FIT are taken from [46, 82], and the solar PV rating is selected as less than 10kW. The brand and type of the EV is Tesla Model S P100, the battery capacity is 100kWh. According to Table. 4 – 6, the battery price of this EV is approximately equal to £25,860. Furthermore, another product of Tesla, which is Powerwall, is selected as the ESS. Each Powerwall has the capacity of 6.4kWh and cost \$3,000 (approximately £2,400). The grid voltage supplied to this home is the standard household AC voltage of UK which is 240V, and the charging / discharging current of EV and ESS are all assumed equal to 10A. The power of the back-up electric heater is

1.1kW for which the rated voltage is equal to the standard home voltage and the current is 5A. According to [129], the smallest area of solar panel is around 16 m^2, so the maximum radiation absorbed area for both of SWH and PV systems are set as 16 m^2. The storage tank's volume for SWH is 80L.

The average hourly residential load curve is shown in Fig. 5 - 3, which is sourced from UK official government's report [33]. The average hourly solar irradiance is sourced from [109], where the area is near Glasgow, UK. The selected months are January for winter case and July for summer case, as shown in Fig. 5 - 4 and Fig. 5 - 5. The average hourly hot water consumption is sourced from[108], as shown in Fig. 5 - 6. The make-up water for the SWH are usually 8 $^\circ$C in winter and 15 $^\circ$C in summer. According to report [130], the average daily indoor ambient temperature are 18.3 $^\circ$C in winter and 21 $^\circ$C in summer, which are used for the case studies.

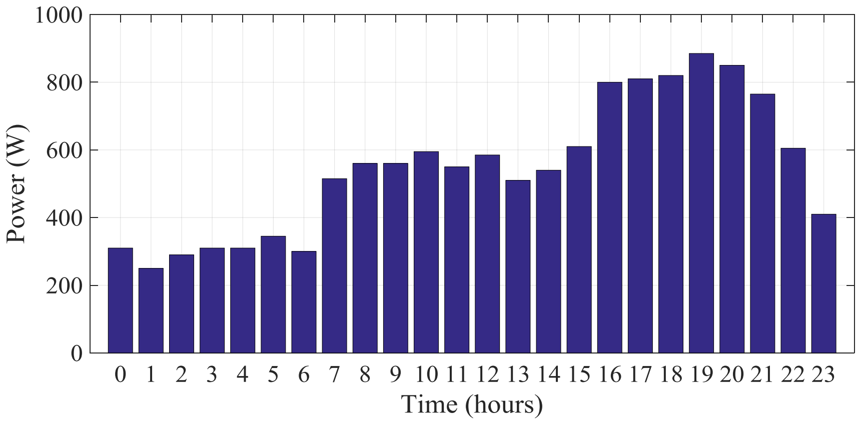

Fig. 5 - 3 Average hourly load variation during a day [33]

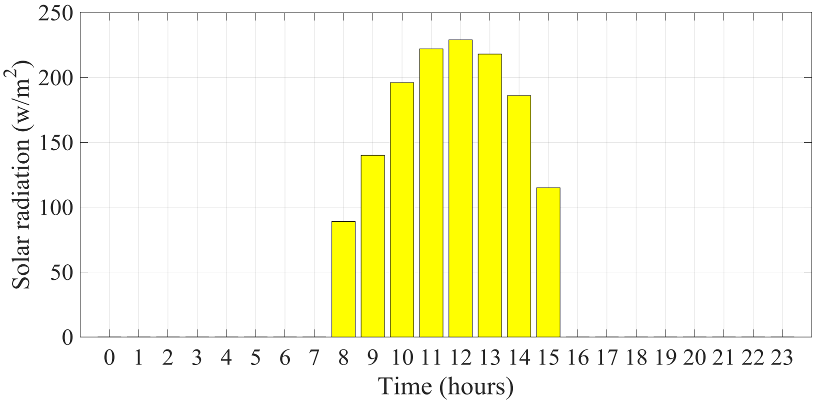

Fig. 5 - 4 Average hourly solar radiation during a day in January [109]

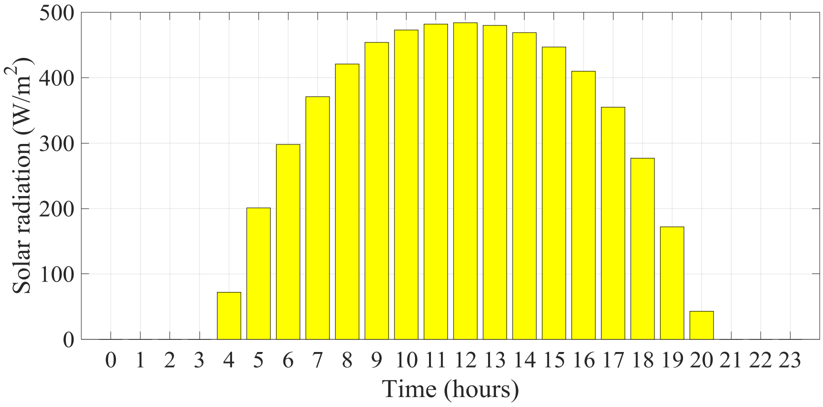

Fig. 5 - 5 Average hourly solar radiation during a day in July [109]

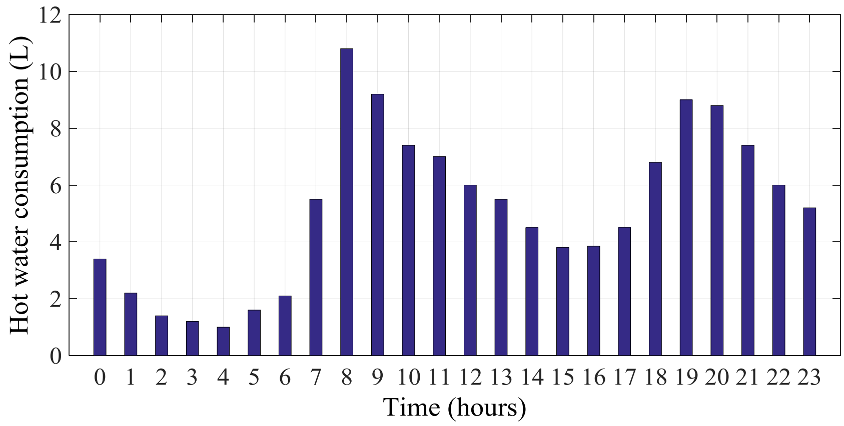

Fig. 5 - 6 Average daily hot water consumption [108]

In the following case studies, the initial SOC of EV and ESS are set as 80% and 0%, respectively. The terminal SOC value of EV is set as 80%. The expected temperature for each sampling time period is set as $50^{\circ}\mathrm{C}$.

5.4.2 Analysis of factors that directly influence the hot water temperature

In this subsection, the factors that directly influence the hot water temperature are analysed. The selected solar collected area is $0m^2$ for SWH and $16\ \mathrm{m}^2$ for PV system. In this simulation, the selected season is winter, the initial water temperature of the storage tank is set as $8^{\circ}\mathrm{C}$. The simulation length is 48 hours, the results are shown in Fig. 5 - 7

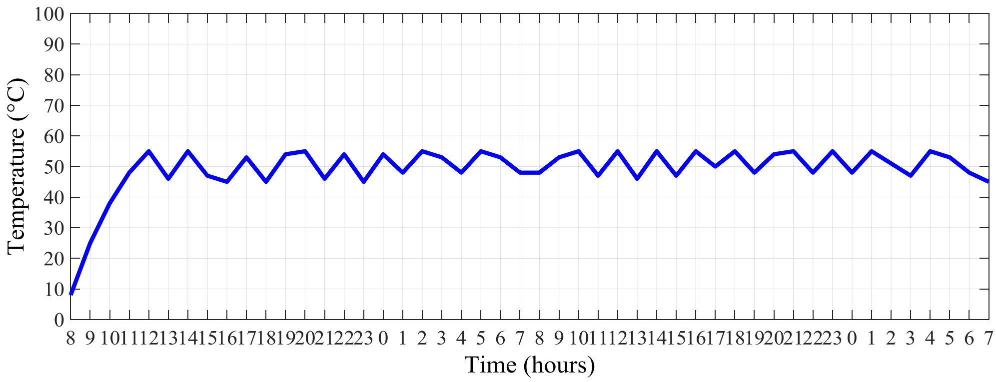

Fig. 5 - 7 Hot water temperature for winter season (48hours)

It shows in Fig. 5 - 7 that since the initial temperature is low, the hot water's temperature keeps on increasing, in the first 4 hours, in order to reach the zone in (5.11). Once the water temperature is close to the expected $50^{\circ}\mathrm{C}$, it fluctuates around this value. In the constraint in (5.11), the constant Z is set as $2^{\circ}\mathrm{C}$, so the hot water's temperature value is only allowed to fluctuate $2^{\circ}\mathrm{C}$ above and below the expected value. In the simulation, the temperature variation exceeds this range. The main reason is that the selected sampling time Δt (1 hour) is too long for an effective adjustment. There are two ways to solve this problem. One is to shorten the sampling time Δt. This is not practical in the simulation since many other data collected are sampled hourly, such as solar radiation, water consumption, and load curve, etc. Besides, it is arguable if the hourly data is simply averaged to half form or quarter form. Another way is to increase the constraint band. In the next simulations, the temperature of the hot water for local usage is allowed to fluctuate 5 $^{\circ}$C, i.e., Z = 5.

According to subsection 5.4.1, the total solar collect area is limited to 16 m^2, so if the collect area for SWH needs to be increased, PV area will be decreased the same amount that is increased in the SWH. Fig. 5 - 8 show the running results with different areas of SWH and PV in winter. It can be seen from Fig. 5 - 8, during the peak solar radiation time, the water temperature increases extremely high with larger area of SWH, and largely exceeds the constraint value. The maximum temperature of water is 100℃, the maximum area for SWH can observed as 9.6 m^2.

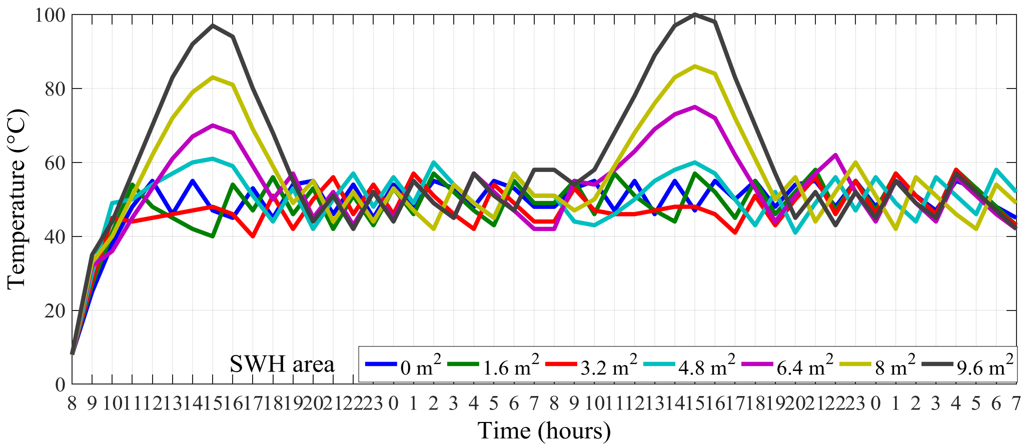

Fig. 5 - 8 Temperature results with different areas of SWH and PV (winter case)

The results for summer period are shown in Fig. 5 - 9, where the maximum SWH area is dropped to 3.2m^2. From both results in winter and in summer, it can be concluded that the absorbed solar radiation is a key factor that directly influences the hot water temperature when SWH is applied. Also, the results prove that large applicable area for SWH system is not necessary in high solar radiation area or in summer season.

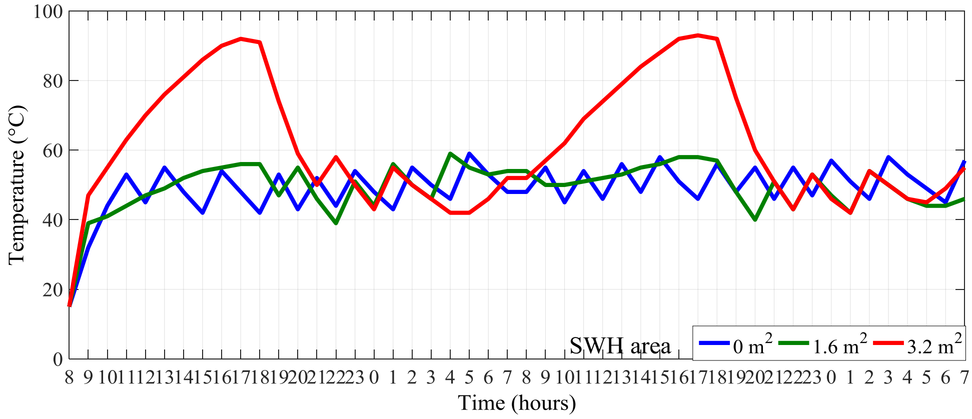

Fig. 5 - 9 Temperature results with different areas of SWH and PV (summer case)

Another factor which directly influences the water temperature is the hot water consumption at each time period. To investigate this influence, a winter case is selected. The SWH area is $4.8\mathrm{m}^2$ and the PV area is $11.2m^2$. The hot water consumption is assumed to the same at all time during one day in order to see the temperature change for different daily consumptions. As can be seen from the results shown in Fig. 5 - 10, the average water temperature in a day decreases when the hot water consumption increases.

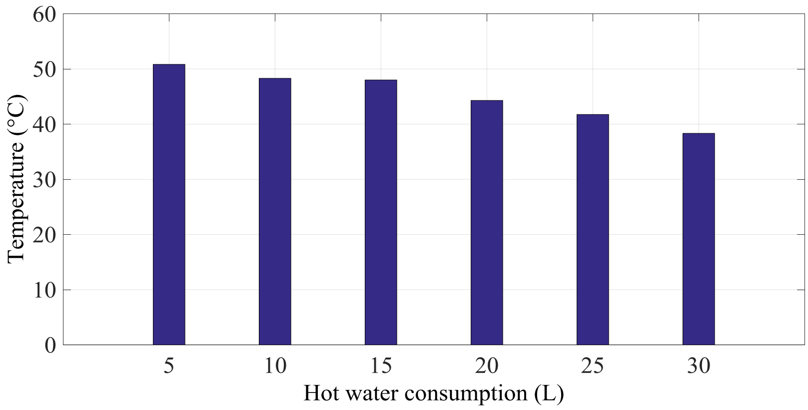

Fig. 5 - 10 Average hourly hot water consumption (L)

5.4.3 Comparison for different areas of SWH and PV

In this subsection, impacts of SWH and PV are analysed. The selected season is winter and the tariff is fixed. To test the impact of PV and SWH separately, PV's area is set as $0\mathrm{m}^2$ at first, which means only SWH is used. Fig. 5 - 11 shows that the daily cost is decreased with the increase of the area of SWH.

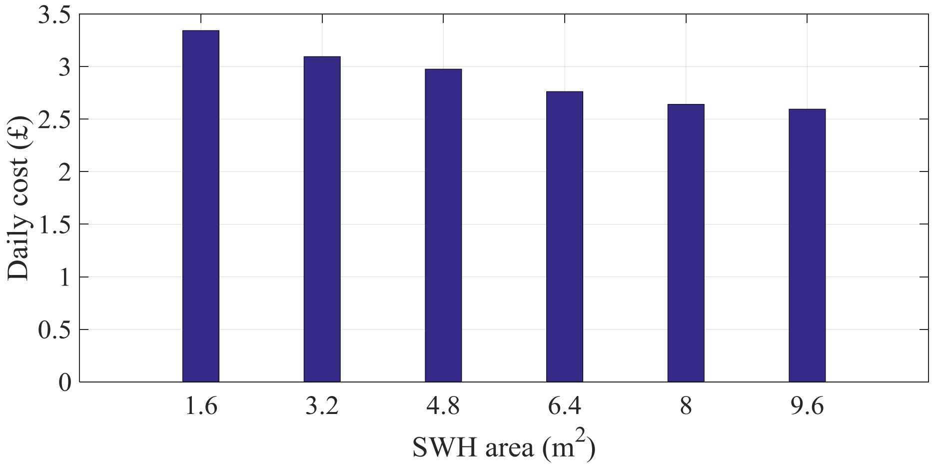

Fig. 5 - 11 Daily cost with different areas of SWH

Then, the SWH's area is set as constant, which is $9.6m^2$. Without considering the total area constraint, the PV's area is varied from 1.6 m^2 to 9.6 m^2. The daily costs results are shown in Fig. 5 - 12, from which it can be seen that the cost also decreases with the increase of the PV area.

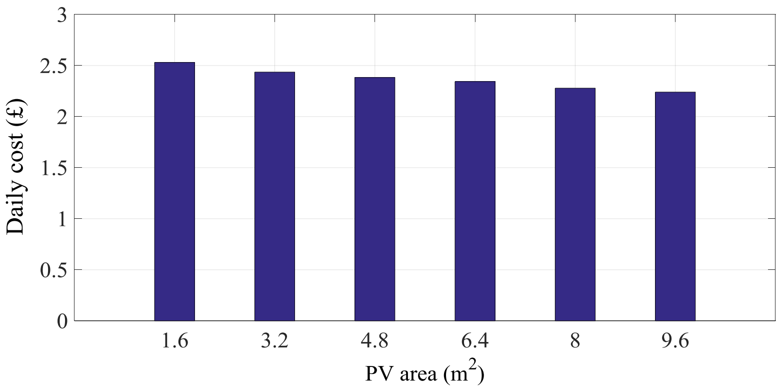

Fig. 5 - 12 Daily cost with different areas of PV

Next consider the situation that the total area for collecting solar radiation is limited by $16m^2$. If user wants to apply SWH and PV together, the PV's area will be decreased by the same amount increased in SWH area. The optimal selection, under which the user's cost is minimum, between SWH area and PV area needs to be determined. Comparing Fig. 5 - 11 with Fig. 5 - 12, it can be observed that larger area of SWH seems to result in higher cost reduction than PV. It can be expected that SWH is more efficient than PV when used for water heating. However, this does not mean that a larger area of SWH is the more cost saving option for the user. This is because the daily hot water consumption is not unlimited, excessive area of SWH will be wasted. Fig. 5 - 13 shows the daily cost comparison in a winter day, under two tariffs, when different areas of SWH and PV are applied. It can be seen from Fig. 5 - 13, if the selected tariff is the fixed tariff, the minimum cost is £2.22 when the optimally selected areas for SWH and PV are $4.8m^2$ and $11.2m^2$, respectively. If the tariff is TOU, the minimum cost is £1.82 and the areas of SWH and PV are $6.4m^2$ and $9.6m^2$, respectively. Fig. 5 - 14 shows the optimised cost results when the selected season is summer. As can be seen from Fig. 5 - 14, no matter which tariff is applied, the best option is $1.6m^2$ for SWH and $14.4m^2$ for PV. Comparing the cost between two different tariffs in both Fig. 5 - 13 and Fig. 5 - 14, the user will obtain more profits if the TOU tariff is applied.

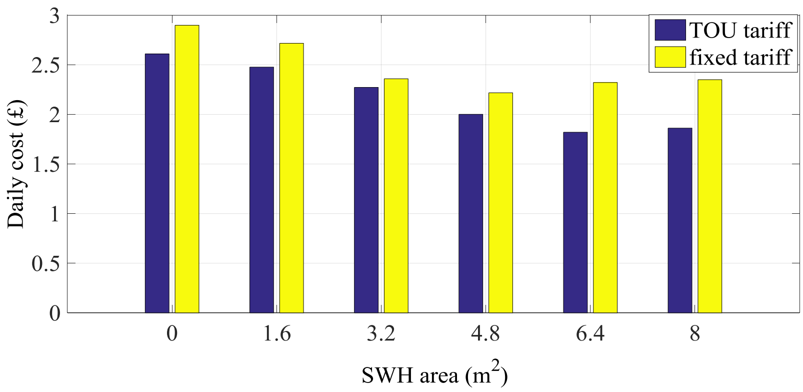

Fig. 5 - 13 Cost comparison of diffrerent SWH's area in winter

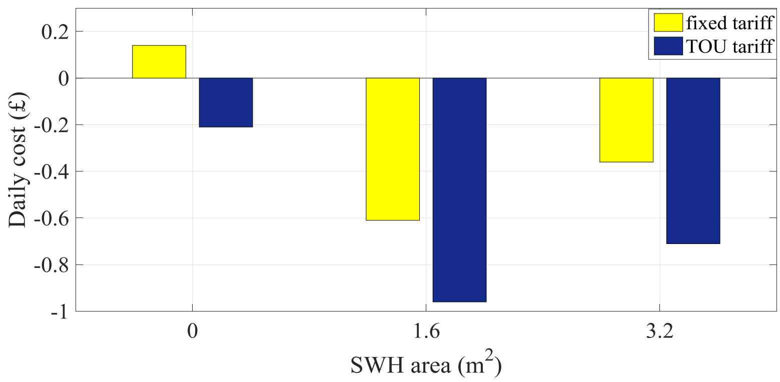

Fig. 5 - 14 Cost comparison of diffrerent SWH's area in summer

Fig. 5 - 15 and Fig. 5 - 16 show the hot water's temperature against time when the tariff is TOU. In summer time, the hourly water temperature fluctuates around the expected temperature, and the variations are mostly within the acceptable range, when

the SWH area is set to be 0 m^2 and 1.6 m^2. In winter time, the suitable SWH area is up to 4.8 m^2.

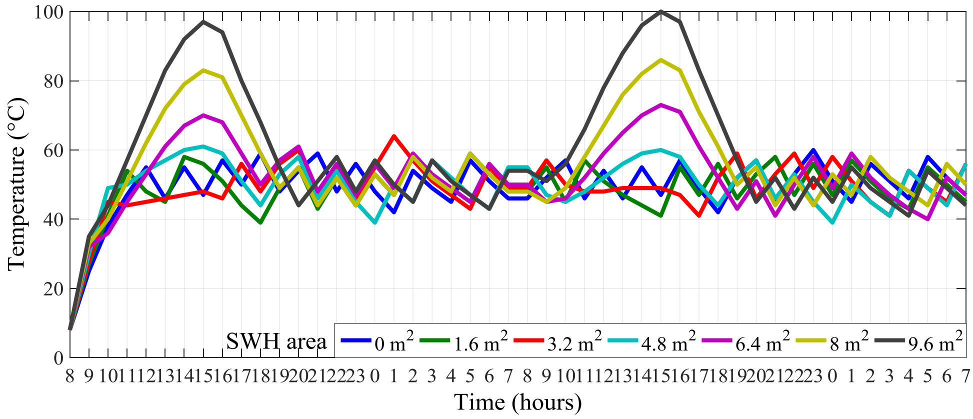

Fig. 5 - 15 Hot Water temperature curve for TOU tariff in winter (different SWH area)

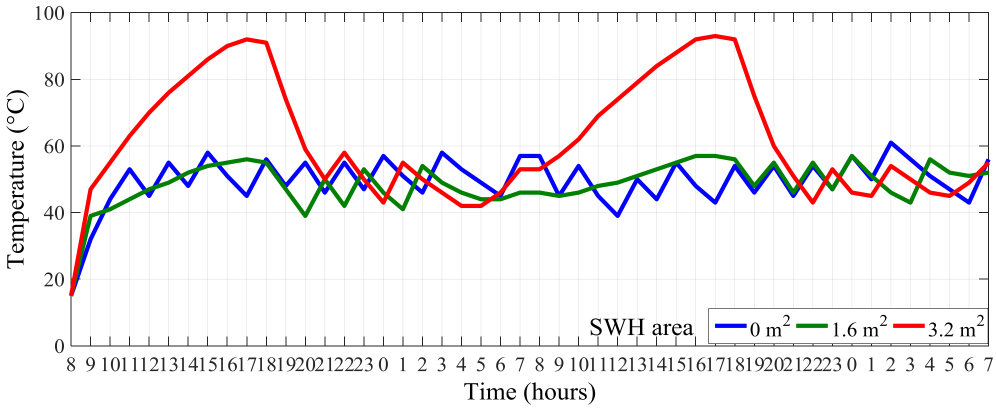

Fig. 5 - 16 Hot water temperature curve for TOU tariff in summer (different SWH area)

5.4.4 Analysis of tank volume, seasonal impacts to SWH area

In this section, the fixed tariff is applied in the simulation. The specific heat capacity c can be described by the ratio of the heat added to (or removed from) an object to the resulting temperature change as follows:

$$c = \frac{E}{M * \Delta T} \tag{5.13}$$

where E is the energy change (J), M is mass of object (kg), and ΔT is the temperature change (℃). The object for SWH is water, the specific heat capacity c is a constant. Assume the temperature change ΔT is constant, then it can be found that the larger mass of water needs more energy added or removed from water. When the energy change E is fixed, larger mass of water will result in less change of temperature. Therefore, the volume of the storage tank in SWH system is another factor that influences the hot water temperature, the user's cost, and the optimal selection of SWH collecting area. Fig. 5 - 17 shows the maximum SWH's area under different volumes of storage tanks, ranging from 80L to 240L.

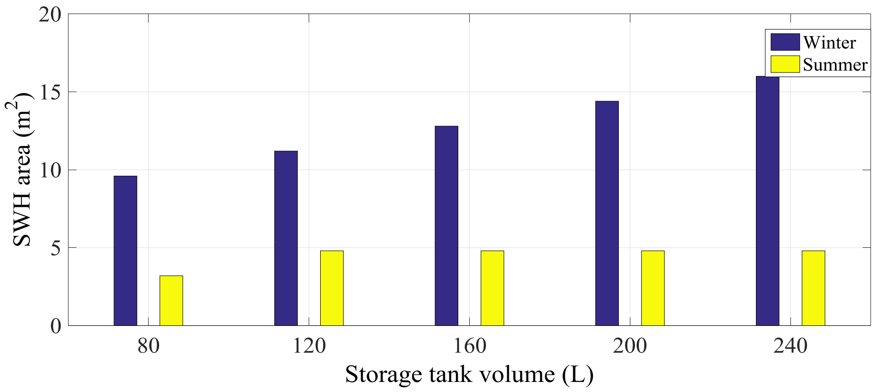

Fig. 5 - 17 Comparison of different volumes of storage tank

From the results in Fig. 5 - 17, it can be seen that larger tank volume can absorb more energy from the solar radiation so the applicable SWH area can be larger. Results on daily costs in winter are shown in Fig. 5 - 18, when different storage volumes and different SWH areas are applied. The best match of SWH and PV, which can achieve the minimum daily cost, can be observed from these figures and Table. 5 - 1.

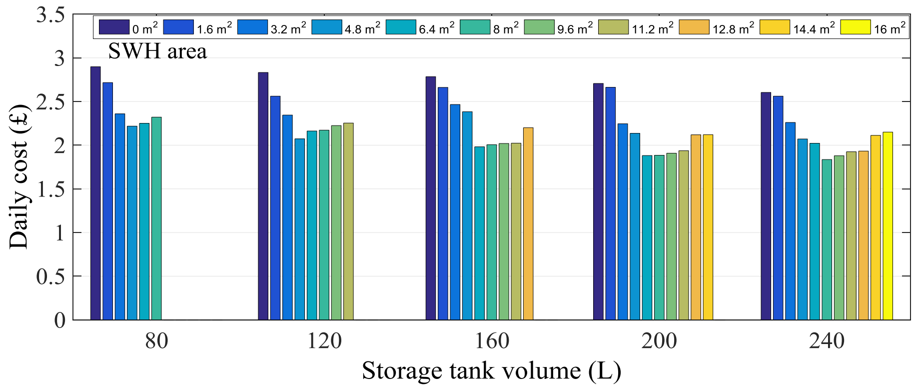

Fig. 5 - 18 Comparison of daily cost for different storage volume and different SWH area in winter

Table. 5 - 1 Optimum match of SWH and PV for different storage volume in winter

Storage Volume (L)	80	120	160	200	240
PV area (m^2)	11.2	11.2	9.6	9.6	8
SWH area (m^2)	4.8	4.8	6.4	6.4	8
Cost (£)	2.22	2.07	1.98	1.88	1.83

As can be seen from Table. 5 - 1, the minimum cost for the end user decreases with the increase of the storage volume. In addition, larger storage volume needs more SWH area to achieve the optimal cost. The best trade-off between SWH and PV's area are shown in the above table. As can be seen from Fig. 5 - 18, the cost is decreased with the increasing area of the SWH. After reaching the minimum cost, the cost will increase if the SWH's area is further increased. The reason is that the SWH's area is already big enough for the water heating usage at the minimum cost point. If the area is increased further, it will waste the available solar panel's area which can be utilised for PV. This result is consistent to the conclusions in subsection 5.4.2 that unnecessary large SWH's area is not suitable for the high solar radiation's area or summer season.

The solar radiations are different at different time of the year; therefore, the optimal areas of SWH and PV for different months are calculated to be different, as shown in Table. 5 - 2. It can be seen that larger area of SWH is required in the low solar radiation months which is autumn/winter period from October to February. The area of SWH is relative low during the spring/summer period from March to September. In order to satisfy the hot water demand throughout the whole year, the average value of SWH's area during the whole year has been selected as the recommended SWH area, which is 30% of total area of the solar panel.

However, in practice, once SWH and PV are installed, their areas cannot be arbitrarily changed; otherwise, the labour costs would be much higher than the savings of energy costs.

Table. 5 - 2 Optimal areas of SWH and PV for different months

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
PV Area	70%	70%	80%	80%	90%	90%	90%	90%	80%	80%	70%	70%
SWH Area	30%	30%	20%	20%	10%	10%	10%	10%	20%	20%	30%	30%
Cost (£)	2.22	1.15	0.16	-0.56	-0.83	-0.72	-0.61	-0.38	0.09	1.51	2.18	2.28

5.4.5 Switch on-off of SWH

According to the above analysis, the area of SWH is selected as 30% of the total available area for solar panel. Using this area setting, the solutions of SWH back-up electricity switch on/off status are shown in Fig. 5 - 19 for summer, and in Fig. 5 - 20 for winter. As can be seen from the results, in order to guarantee the daily hot water demand, the back-up electricity will be switched on more often in winter than in summer. This is mainly because the solar radiation is much less in winter. In addition, no matter during summer or winter, the SWH back-up electricity is switched on more often during night time, when the hot water demand still exists but there is no solar radiation. In this case study, the solutions are obtained based on the average daily hot water consumption from multiple end users, which is shown in Fig. 5 - 6. However, the habits of hot water consumption are different from case to case, the optimal solutions for each single end users will also be different.

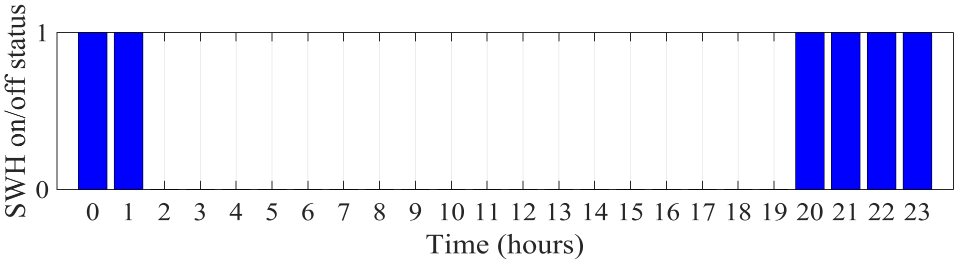

Fig. 5 - 19 SWH back-up switch on/off status in July

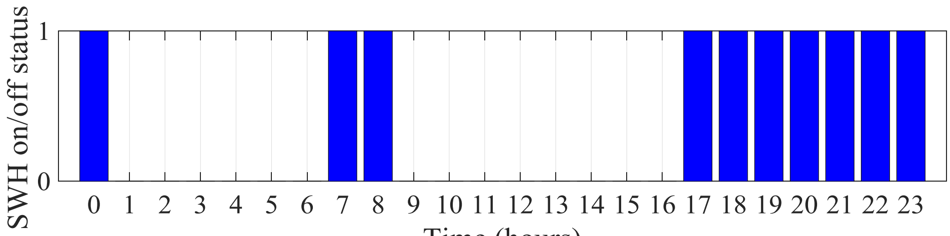

Fig. 5 - 20 SWH back-up switch on/off status in January

5.4.6 Comparison with PV-T hybrid system

In this subsection, the options of PV-T and PV - SWH in cost reduction has been discussed. The storage tank's volume is 80L, the selected EV is TESLA MODEL S 100. The thermal part of PV-T system model is assumed similar to SWH model in (5.7). The electrical conversion efficiency of the PV-T system is selected to be 10% higher than the PV system as suggested in [122]. The thermal efficiency of the PV-T system is 5% lower than the SWH system sourced from [124]. Therefore, for the PV-T mathematical model, the PV power equation (4.2) and the absorbed radiation equation (5.4) should be rewritten as:

$$P_1(i) = \lambda \cdot I(i) \cdot A \cdot 110\% \tag{5.14}$$

$$S(i) = (\tau\alpha) \cdot I(i) \cdot 95\% \tag{5.15}$$

The minimum daily cost of the end user is calculated by the optimisation route in (5.12). Table. 5 - 3 shows the annual cost for two different hybrid systems. Table. 5 - 4 show the daily cost results in each month. It can be seen that the cost of PV-T is lower than the PV-SWH system. The end user can make profit with the PV-T system is installed. However, the initial investment cost of PV-T is much higher than the traditional PV or SWH system. Whether the PV-T system can benefit the end user from long-term perspective should be analysed. In this thesis, details of relevant financial analysis are presented in next chapter.

Table. 5 - 3 Annual cost comparison between PV-T and PV-SWH

PV-T Annual cost (£)	-140.5
PV-SWH Annual cost (£)	197.4

Table. 5 - 4 Daily cost comparison between PV-T and PV-SWH for different month (£)

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
PV-T Cost	1.92	0.61	-0.72	-1.96	-2.53	-2.22	-1.98	-1.52	-0.86	0.95	1.77	1.92
PV-SWH Cost	2.22	1.15	0.16	-0.56	-0.83	-0.72	-0.61	-0.38	0.09	1.51	2.18	2.28

5.4.7 Comparing with non-optimised solution

The results between optimised and non-optimised options are compared in this section. In non-optimised calculation, simply add together each power consumption and PV power generation at all times, and then multiply the sum by the electricity tariff or FIT. Therefore, the daily total cost can be obtained through the summation of the cost over all time intervals. In order to obtain a reasonable comparison, the initial input data of the non-optimised calculation are chosen to be the same as the optimised calculation, such as solar radiation, load curve, electricity tariff. The SWH is ignored but the PV system is included in the non-optimised solution, which means all of the solar panel area is utilised for the PV system. Following [131], the power consumption for water heating has been included with EWH. In addition, ESS is not included in the non-optimised calculation and the EV relevant part is fixed.

Table. 5 - 5 shows the annual cost comparison between the optimised and non-optimised results. It can be seen that the cost of user can be effectively reduced. When

PV-T system is adopted, the annual cost will be reduced 100% and end user can make profit around £140 per year.

Table. 5 - 5 Annual cost comparison between optimised and non-optimised results

System type	Optimised Annual Cost (£)	Non-optimised Annual Cost (£)	Cost Reduction
PV-SWH	197.4	890.4	77%
PV-T	-140.5	890.4	100%

5.5 Summary

In this chapter, the residential home cost reduction system has been expanded to include solar energy supply. The hourly hot water temperature under optimal control for different area of solar thermal collector is obtained, and the factors that influence the water temperature are investigated. The sufficient areas of solar thermal collector for different seasons are calculated. It's been found that larger area of SWH are unnecessary for area with strong solar radiation since PV system can be used to achieve cost reductions. Comparing SWH with PV, the results show that SWH is more efficient than PV when transfer the solar energy for water heating. Therefore, solar thermal water heater is still necessary to achieve the economic benefit for the end users but the area should be limited.

Both TOU and fixed electricity tariffs are applied in the case studies, and it has been shown that the user will obtain more benefit under the TOU tariff. In addition, the trade-off decision between the SWH area and the PV area is made based on the modelling framework. The case study shows that the volume of water storage tank has influence on choosing the area of solar thermal collector.

Moreover, the hybrid PV-T system is compared to PV – SWH system. Results show that the hybrid PV-T system can achieve more cost savings than the combination of PV and SWH systems. The cost which is obtained through the optimised has been compared with the non-optimised model, and the results show that the optimised setting can reduce the cost by at least 77% for a typical residential home.

Chapter 6 Financial Analysis of the Household Energy System

In the previous two chapters, minimisation of residential home energy cost has been explored considering EV, ESS and PV. Through the developed optimisation framework, the energy cost can be minimised by scheduling of charging and discharging of EV and ESS batteries, switch on and off of SWHs, optimal setting of SWH area. However, initial investments of the equipment, such as PV, SWH and ESS, are usually very high. Whether the cost savings calculated from the optimisation route can compensate the investments can be an issue. In this chapter, three appraisal methods are applied to assess and analyse the investment worth of the residential energy system. The basics of appraisal methods are introduced in Section 6.1. Section 6.2 presents the financial model of the residential energy system. Results and analysis of the residential home energy system are discussed in Section 6.3. Conclusions are given in Section 6.4.

6.1 Fundamentals of appraisal method

In this section, fundamentals of several appraisal methods are introduced, including payback period (PB), discounted payback period (DPB) and net present value (NPV).

6.1.1 Payback period (PB) and discounted payback period (DPB)

The initial investments of SWH, PV, and ESS for a smart home are usually very high even though they could bring benefits for the residential users. Also, the operation costs, maintenance costs and replacement costs of the storage battery need to be considered by the end-users to see whether they could save money comparing with using the traditional home energy systems. For this purpose, appraisal methods need to be applied to analyse the investment worth. The PB is one appraisal method that considers the period of time taken for the future net cash inflows to match the initial cash outlay [132]. For example, company A wants to purchase a new machine with a cost of £40,000, which can generate the operating cash flow of 16,000 in each subsequent year. The payback period of this newly purchased machine can be analysed by the cash flow. Table. 6 - 1 gives the annual cash flow and cumulative cash flow for this project.

Table. 6 - 1 Annual cash flow and cumulative cash flow

Year	OPF (£)	Cumulative cash flow (£)
0	-40,000	-40,000
1	16,000	-24,000
2	16,000	-8,000
3	16,000	8,000

There are two approaches of PB, the short cut method and the unequal cash flow method. The short cut method is applied when the amounts of annual operating cash flows expected from a potential capital asset acquisition are equal each year. For the above example, the annual operating cash flows are equal each year, so the short cut calculation can be used to determine the payback period as shown in (6.1).

$$PB = \frac{C_I}{OPF} \tag{6.1}$$

where C_I is the initial investment such as the equipment cost and the installation cost. OPF is the annual operating cash flow (OPF), which refers to the amount of cash inflows and outflows within the life cycle of an investment project after it is put into operation. The cash inflows refer to the operating cash income which is positive amount, and the cash outflows refer to operating cash expenses and taxes paid which are negative amount. Equation (6.1) is used to calculate the payback period of the earlier example, and the PB result is 2.5 years.

Another approach is called unequal cash flows method, which deals with the amount of operating cash flow that are not expected to be the same amount each year. The method begins with the acquisition cost, and subtract the expected cash flows for each year until the point in time that all of the cash has been recovered. The portion of final recovery year is calculated and the payback period is equal to the number of full years plus the portion of final recovery year. According to the second method, it can be observed form Table. 6 - 1 that the cumulative cash flow for this project reduces to -£8,000 at the end of year 2, and improves to £8,000 at the end of year 3; therefore, the payback period can be calculated by

$$PB = (2 + \left|\frac{-8,000}{16,000}\right|) \ = 2.5$$

The result is the same as the first method.

There are good reasons of using the PB method for business analysis. First it is simple to understand and calculate. It can help managers to make a quick evaluation on projects. Second, the PB can be used to compare the relative risk of projects with varying periods, which is essentially a popular measure of risk, and can help the analyst to determine how quickly money can be returned from an investment.

Although PB is one of the most popular and simple methods to analyse the return-of-investment, there are problems with PB as a measure of investment worth. According to [133, 134], one of the serious problems is that the time value of money (TVM) is ignored in PB. TVM is the concept that receiving money at the present time is of greater benefit than the same amount in the future because of its potential earning capacity. This principle of TVM explains why money can earn interest, which can be expressed by the following formula.

$$FV = PV \cdot (1 + \frac{r}{n})^{n \cdot t} \tag{6.2}$$

where FV is the future value of money; PV is the present value of money; r is the interest rate; n is number of compounding periods per year; t is the number of years. For example, assume the invested cost is the same as in the previous example for 2.5 years at 8% interest, which is £40,000, and the number of compounding periods is 2 per year, then the future value of that money can be calculated as

$$FV = 40,000 \cdot (1 + \frac{8\%}{2})^{2.5*2} = 48,666$$

In this case, the future value of this money, £48,666, is more than two and half years ago; therefore, the net cash inflows cannot match the future value of the initial cash outlay when the payback period is 2.5 years.

Another limitation in PB is that the payback analysis fails to compare the overall profitability of two different projects because the inflows of cash that occur beyond the payback period are not considered in the analysis. For two proposed investments which might have similar payback periods, the cash inflows of one project might steadily decline after the end of its payback period, and the other project's cash inflows might steadily increase after its payback period. Many capital investments may require the investment returns over years that are much longer than the payback period. Therefore, the PB analysis cannot be the only measure of the return-of-investment. In addition, the cash flows that occur with capital investments are full of complexities which are not taken into account in the PB analysis. For example, the PB analysis only considers one large cash outflow followed by steady cash inflows thereafter, but additional cash outflows may be required and inflows may fluctuate in accord with sales and revenues [135]. Due to these limitations and drawbacks, the PB method is usually used as the preliminary evaluation, and other appraisal methods should be considered as the supplemented evaluations, such as DPB and NPV.

To counter the error caused by TVM, the DPB method is usually applied. It can help the analyst to calculate the result to break even in a project by discounting future cash flows and recognising the TVM. It reflects the amount of time to break even in a project not only based on cash flows, but also when they occur and the prevailing rate of return in the market [135]. Equation (6.3) shows the calculation of discounted cash inflow for each period.

$$DCI = \frac{OPF}{(1+dr)^{\chi}} \tag{6.3}$$

where DCI is the discounted cash inflow; OPF is operating cash flow; dr is the discounted rate; χ is the period to which the cash inflow relates. It can be noticed that the discounted rate, dr, and the cash inflow related period, χ, are the crucial factors that influence the cash value. The term $\frac{1}{(1+dr)^{\chi}}$ can be considered as the cash inflow value factor.

Back to the previous example shown in Table. 6 - 1. Assuming the discounted rate, dr, is 8%. The cash inflow value factor, the discounted cash inflow, and the cumulative discounted cash inflow can be calculated, and shown in Table. 6 - 2.

Table. 6 - 2 Annual discounted cash inflow and cumulative discounted cash inflow

Year	*OPF* (£)	Cash inflow factor ω	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-40,000	1	-40,000	-40,000
1	16,000	0.9295	14,872	-25,128
2	16,000	0.8573	13,717	-11,411
3	16,000	0.7938	12,701	1,290

According to the unequal cash flows method, the discounted payback period can be calculated as:

$$DPB = (2 + \left|\frac{-11411}{12701}\right|) \text{ years} = 2.9 \text{ years}$$

It can be seen that the discounted payback period is longer than the traditional payback period, and the result is more reliable since it accounts for TVM. However, it still ignores the cash inflows from project after the payback period; therefore, the method of NPV is applied to analyse the profitability of the investment or project as the supplemented evaluation.

6.1.2 Net present value

NPV is defined as the difference between the present value of cash inflows and outflows over a period of time [132, 136]. This method is usually applied to evaluate the desirability of investment opportunities. Project managers can make decisions whether the investment should be accepted or rejected depending on the results calculated through this method. The NPV index can be expressed as:

$$NPV = \frac{OPF_1}{1+r} + \frac{OPF_2}{(1+r)^2} + \frac{OPF_3}{(1+r)^3} +, \ldots, + \frac{OPF_t}{(1+r)^t} - C_I = \sum_{t=1}^{n} \frac{OPF_t}{(1+r)^t} - C_I \tag{6.4}$$

where OPF_t is the operating cash flow during the time period t; C_I is the total initial cost of investment; n is the project's life and r denotes the required rate of return-of-investment, which can also be called the discount rate. As can be seen from the above equation that the NPV of a project is determined by three factors: the sum of the net annual cash flows, the discount rate and the initial outlay. A positive NPV means that if the earnings generated by the project exceeds the initial cost, then it will be a profitable investment. On the other hand, the investment with a negative NPV will result in a net loss, and it should be rejected by the decision maker. Fig. 6 - 1 shows the decision chart following NPV.

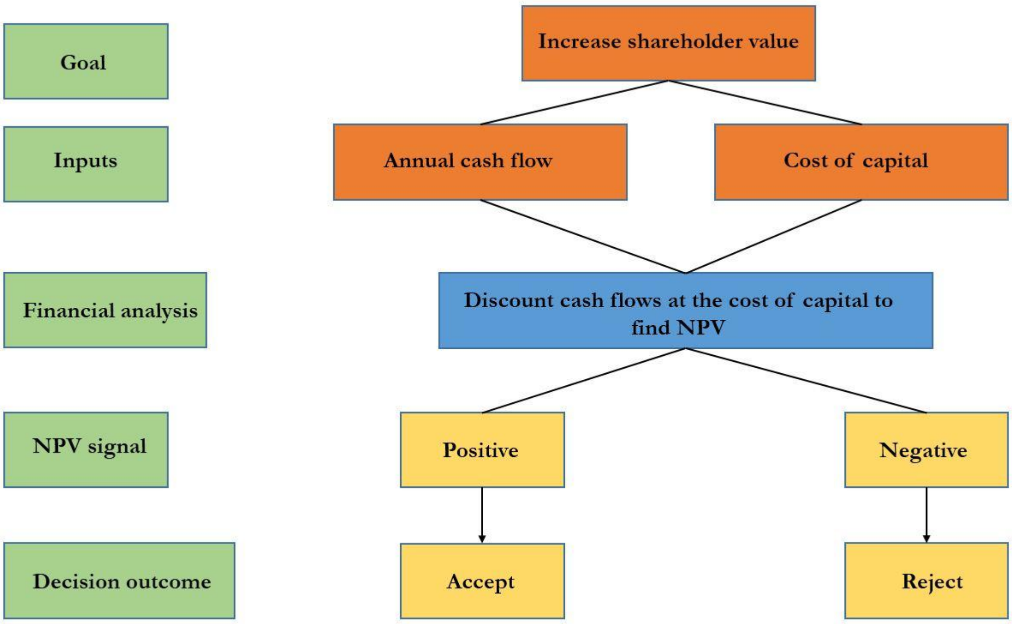

Fig. 6 - 1 Decision chart of NPV

Using the same example in this chapter that company A wants to purchase a new machine with a cost of £40,000, which can generate the operating cash flow of 16,000 in each subsequent year. However, at the end of the third year, the machine will be sold in £10,000, and the discount rate is 8% for each year. According to the above information, the annual cash flows of company A and the NPV can be calculated as shown in Table. 6 - 3, from which it can be seen that the NPV is positive at the end of the third year; therefore, the investment of this new machine can be accepted by the manager.

Table. 6 - 3 Aannual cash flows and NPV of company

Year	*OPF* (£)	Discount factor $\frac{1}{(1+r)^t}$	Present value of cash flow (£)
1	16,000	0.9295	14,872
2	16,000	0.8573	13,717
3	16,000	0.7938	12,701
Total present value of cash flow (£)			41,290
Initial investment (£)			-40,000
NPV at the end of third year			+1,290

6.2 Financial model of the household energy system

The optimisation design in Chapter 4 and Chapter 5 aim to minimise daily energy cost of residential home end-users. The cost savings come from the decrease in energy costs, which in turn, increase the income; therefore, they are taken as operating cash income. Equation (6.5) expresses OPF for investigating the payback period of the smart home energy system.

$$OPF = C_s - C_m \tag{6.5}$$

where C_s is the annual cost savings; C_m is the annual maintenance fees of the smart home system. The annual cost savings can be calculated by (6.6), and the relevant data can be obtained from the results in Chapter 5.

$$C_s = C_{non-opt} - C_{opt} \tag{6.6}$$

Here $C_{non-opt}$ is the annual cost following a standard setting without optimisation; C_{opt} is the annual cost obtained by the optimised solution. In addition, the energy cost model built in Chapter 4 includes all the energy consumption costs of the household, such as cost of EV driving and household load demand. The non-optimised annual cost, $C_{non-opt}$, should include both fuel consumption of traditional vehicle and electricity consumption of the household user, which can be expressed as:

$$C_{non-opt} = C_e + C_{driving} \tag{6.7}$$

where C_e is the annual electricity cost without optimisation, $C_{driving}$ is the annual fuel consumption cost of the traditional vehicle.

According to the smart home system built in Chapter 5, the initial investment of this system can be written as:

$$C_I = ic_{pv} + ic_{ess} + ic_{charging} + ic_{control} \tag{6.8}$$

where ic_{pv}, ic_{ess} are the installation costs of PV and ESS, respectively. $ic_{charging}$ is the installation cost of EV home charging system, and $ic_{control}$ is the installation cost of the smart home control system.

The payback period and the NPV for the smart home can be rewritten as:

$$PB = \frac{ic_{pv} + ic_{ess} + ic_{charging} + ic_{control}}{C_e + C_{driving} - C_{opt} - C_m} \tag{6.9}$$

$$NPV = \sum_{t=1}^{n} \frac{\left(C_e + C_{driving} - C_{opt} - C_m\right)_t}{\left(1+r\right)^t} - (ic_{pv} + ic_{ess} + ic_{charging} + ic_{control}) \tag{6.10}$$

6.3 Financial analysis of the residential home energy system

In this section, the investment worth of the residential energy system is assessed by the appraisal methods introduced in section 6.2. The relevant input data, such as OPF, initial investment, and annual maintenance cost is calculated and collected. Financial analysis for different scenarios are compared and discussed.

6.3.1 System specifications

Two types of electricity tariff are considered in the financial analysis, and their values have been shown in Fig. 4 - 5, Chapter 4. In this case study, the smart home system considered does not include SWH and the solar PV's rating is selected to be less than 10kW. Following [137], the solar panel area is selected as 16 m^2 for a house. Each Powerwall has the capacity of 6.4kWh and the cost of $3,000 (approximately £2,400). In the following case studies, the ESS capacity has been expanded through the connection of multiple Powerwall, i.e. 4 Powerwall packs, so the total capacity is 25.6kWh and the cost is around £9,600. Several types of EVs have been selected, which are based on quoted prices of the retailer in UK. In addition, the relevant prices of the battery are estimated by reference [120].The relevant prices' details have been shown in Table. 6 - 4. To analyse the benefits of the household over a whole year, the monthly solar radiation variations need to be considered, and the average hourly solar radiation in each month is shown in Fig. 3 - 5. Furthermore, the average hourly residential load is shown in Fig. 4 - 6.

Table. 6 - 4 Prices of different EV's battery

Brand	TESLA75	TESLA100	BMW I3	SMART	LEAF
Capacity (kWh)	75	100	33	17.6	40
Projected EV Price (£)	64,700	86,200	34,070	21,465	21,990
Evaluation Price of Battery(£)	19,410	25,860	10,221	6,440	6,597
Unit Capacity Cost (£/kWh)	258.8	258.6	309.7	365.8	164.9

6.3.2 Energy cost of traditional household system

A traditional household usually has no self-power supply equipment, such as PV and small wind turbine, and its electricity power is usually provided by external power grid. In addition, the end users of traditional household may also use natural gas for cooking or heating, and the vehicles they select are usually combustion vehicles. The energy consumption can be divided into three parts: electricity consumption, natural gas consumption and petrol/diesel consumption. In this case, it is assumed that the natural gas load is powered by or converted into electric power, such as cooking and heating, therefore only electricity consumption and petrol/diesel consumption for driving are considered.

The end user's daily cost of the electricity consumption can be calculated from equation (6.11) as shown below:

$$C_{electricity} = \sum_{i=1}^{24} P_{load}(i) \cdot \mu(i) \tag{6.11}$$

where $P_{load}(i)$ is the hourly electricity consumption during time period i; $\mu(i)$ is the electricity tariff during time period i. The daily costs of electricity consumption are calculated to be £1.99 for the fixed tariff, and £1.87 for the TOU tariff. The annual cost of electricity consumption, C_e, is calculated through the daily cost multiplied by 365, which are £726.35 and £682.55 for fixed and TOU tariff, respectively.

The probabilities of monthly car fuel costs are obtained through the same survey used in Chapter 4, which are shown in Table. 6 - 5. In order to simplify the calculations, the median value for each spending interval is applied; therefore, the results of expected value of the car fuel costs are calculated based on the median value, which are also shown in Table. 6 - 5. The total annual energy cost for a household includes both of the electricity cost and the car fuel cost, see also(6.7). With fixed and TOU tariffs, the annual costs are £2,472.35 and £2,428.55, respectively.

Table. 6 - 5 Monthly car fuel costs

Monthly car fuel costs	Probabilities	Median value(£)	Expected value(£)
less than £40	5%	20	1.0
between £41 and £80	26%	60	15.6
between £81 and £160	36%	120	43.2
between £161 and £240	16%	200	32.0
between £241 and £300	11%	270	29.7
between £300 and £500	6%	400	24.0
Total monthly expected cost			145.5
Total annual expected cost, $C_{driving}$			1746

6.3.3 Energy cost of smart home without/with optimisation control

To calculate the energy cost of smart household without optimisation control, equation (4.28)in Chapter 4 has been applied in this case. Both of EV charging costs duet to driving, $C_{EV-driving}$, and the average daily battery degradation costs for EV, $C_{EV-average}$, are sourced from Section 4.5.8. The daily costs of the electricity consumption for different months under the fixed tariff without optimisation have been calculated and shown in Table. 6 - 6. Typical EV models are included in this analysis. It is observed that the cost is the lowest for SMART owners, and highest for TESLA 100kWh owners.

Table. 6 - 6 Daily energy consumption cost of different month under fixed tariff without optimisation (£)

EV Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
BMW I3	2.49	2.09	1.61	1.06	0.73	0.79	0.97	1.31	1.60	2.07	2.31	2.64
SMART	2.43	2.03	1.56	1.00	0.66	0.74	0.91	1.26	1.54	2.02	2.25	2.58
LEAF	2.56	2.17	1.69	1.14	0.80	0.87	1.05	1.39	1.67	2.15	2.39	2.71
TESLA75	3.03	2.64	2.16	1.61	1.27	1.34	1.52	1.86	2.15	2.62	2.85	3.18
TESLA100	3.32	2.92	2.45	1.89	1.56	1.63	1.81	2.15	2.43	2.91	3.14	3.47

Since the residential load curve is the averaged profile for all days in a year, the cost per month for different EV models can be obtained through multiplying the daily cost by 30. Fig. 6 - 3 show the monthly and annual cost for different EV models without optimisation under the fixed tariff. It can be seen that no matter which EV is selected, the end user spends lowest in May because the solar radiation is highest during this month.

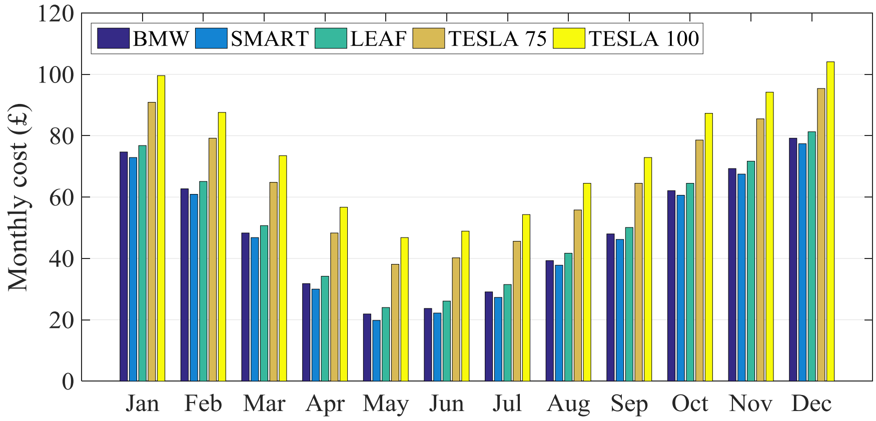

Fig. 6 - 2 Energy consumption cost for different months under fixed tariff without optimisation

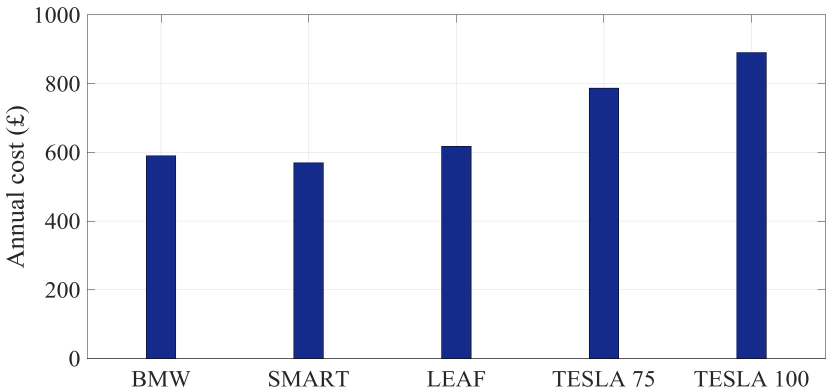

Fig. 6 - 3 Annual energy consumption cost under fixed tariff without optimisation

If the electricity tariff is TOU, we assume the EV is only charged during the night time, so only the night time tariff is applied for charging EV. Same to the case of fixed tariff, the daily costs of the electricity consumption during different months under the TOU tariff without optimisation are also calculated through (4.28), which are shown in Table. 6 - 7. Since the residential load is the averaged value for all days, the cost per month for different EV models is calculated by multiplying 30 to the daily cost. Fig. 6 - 4 and

Fig. 6 - 5 show the monthly and annual costs for different EV models without optimisation under the TOU tariff.

Table. 6 - 7 Daily energy consumption cost of different month under TOU tariff without optimisation (£)

EV Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
BMW I3	1.85	1.52	1.08	0.46	0.11	0.21	0.37	0.73	1.04	1.50	1.69	1.97
SMART	1.75	1.42	0.98	0.37	0.02	0.11	0.27	0.63	0.94	1.39	1.59	1.87
LEAF	1.81	1.48	1.03	0.42	0.07	0.16	0.33	0.68	0.99	1.45	1.65	1.93
TESLA75	2.27	1.95	1.50	0.89	0.54	0.63	0.80	1.15	1.46	1.92	2.12	2.39
TESLA100	2.53	2.20	1.76	1.14	0.80	0.89	1.05	1.41	1.72	2.18	2.38	2.65

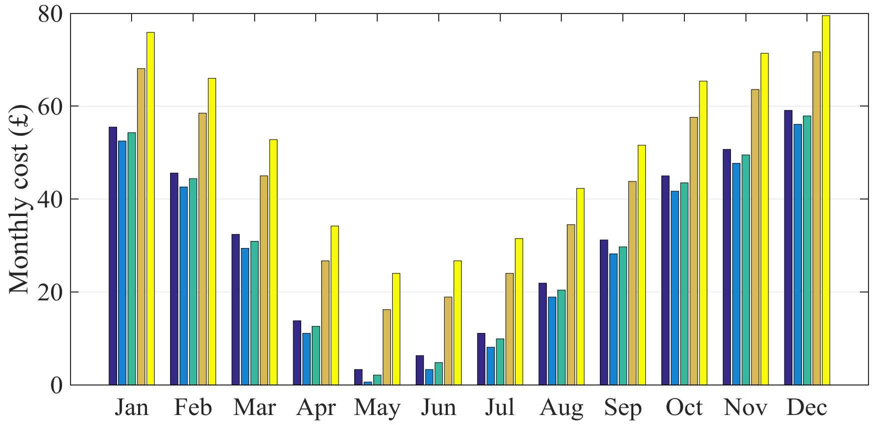

Fig. 6 - 4 Energy consumption cost for different months under TOU tariff without optimisation

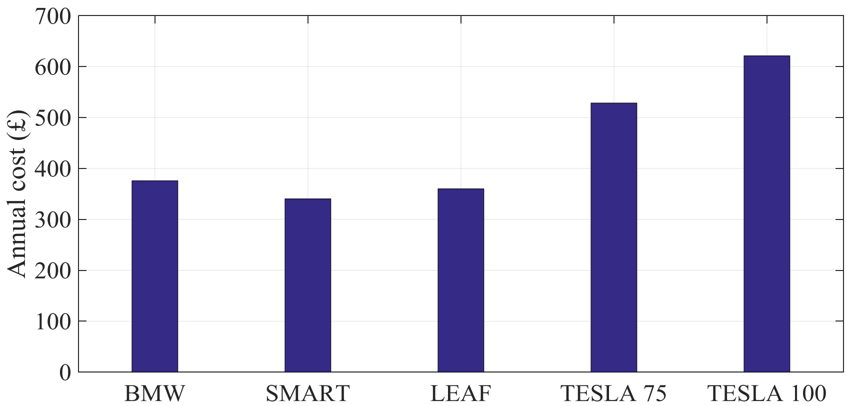

Fig. 6 - 5 Annual energy consumption cost under TOU tariff without optimisation

It is noted that the most economic EV models is still the SMART when the electricity tariff is TOU and the EV is charged during the night time. There are two reasons that can explain why SMART is most economic for EV owners. Firstly, its battery degradation cost is the lowest compared to other EVs as can be seen from Fig. 6 - 6. Secondly, its driving efficiency is the highest compared with other EVs as shown in Table. 4 - 11.

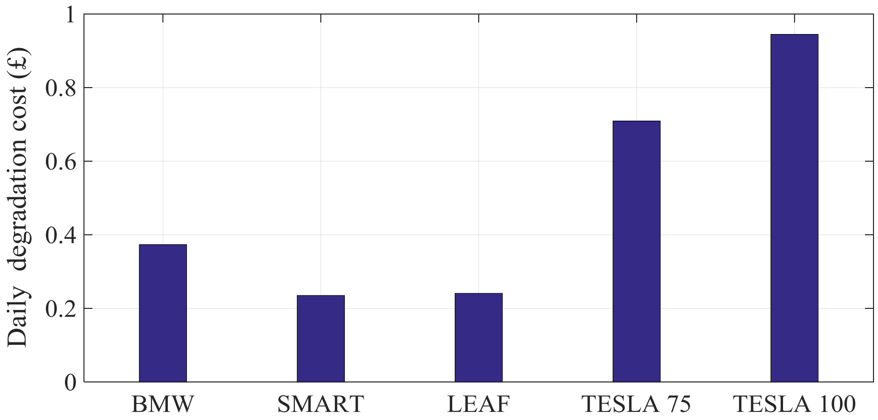

Fig. 6 - 6 Battery degradation cost for different EVs

Table. 6 - 8 shows the charging costs for different types of EV for the same driving distance of 100 miles. It is found that the charging cost for SMART is the lowest. This advantage will be more obvious when the electricity price is high.

Table. 6 - 8 Charging costs for different types of EVs for the same distance driving

Brand	TESLA100	TESLA75	BMW I3	SMART	LEAF
Charging Cost (£)	3.87	3.75	3.55	2.70	3.62

According to the residential home energy cost optimisation in Chapter 4, the overall cost of the end user can be reduced through the optimal scheduling of battery charging/discharging for EV and ESS. The solar radiation data in Chapter 4 is the averaged January data of several years. In order to obtain the annual minimum cost for the end user, other month's solar radiation data need to be considered to recalculate the minimum cost of each month. Table. 6 - 9 and Table. 6 - 10 show the optimised daily costs, over 12 months, under the fixed tariff and the TOU tariff, respectively. Table. 6 - 11 show the optimised annual costs for several EVs. Fig. 6 - 7 and Fig. 6 - 8 show the monthly costs after optimisation under the fixed and the TOU tariffs, respectively

Table. 6 - 9 Daily energy consumption cost of different month under fixed tariff after optimisation (£)

EV Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
BMW I3	2.23	1.22	0.20	-0.70	-0.90	-0.76	-0.63	-0.36	0.02	1.61	2.18	2.26
SMART	2.17	1.15	0.15	-0.71	-0.99	-0.83	-0.71	-0.44	-0.04	1.55	2.11	2.21
LEAF	2.21	1.19	0.18	-0.70	-0.99	-0.83	-0.71	-0.44	0.00	1.58	2.16	2.25
TESLA75	2.64	1.62	0.60	-0.28	-0.57	-0.41	-0.29	-0.02	0.43	2.01	2.61	2.67
TESLA100	2.71	1.69	0.67	-0.22	-0.51	-0.34	-0.22	0.04	0.49	2.08	2.66	2.74

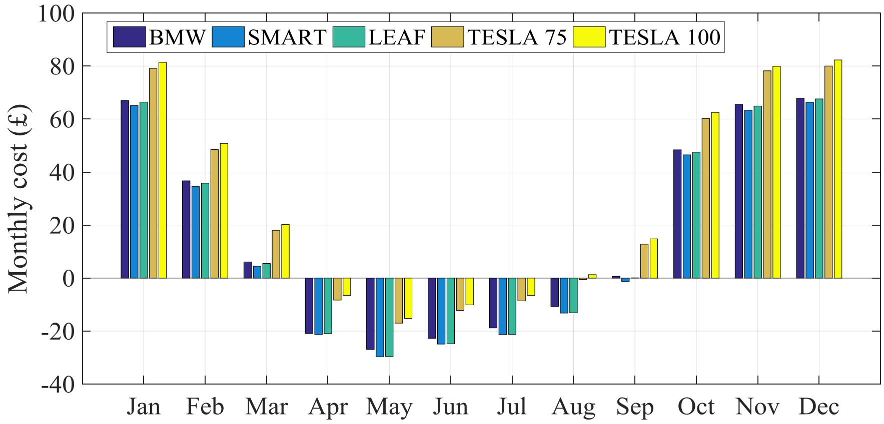

Fig. 6 - 7 Energy consumption cost for different months under fixed tariff after optimisation

Table. 6 - 10 Daily energy consumption cost of different month under TOU tariff after optimisation (£)

EV Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
BMW I3	1.65	0.63	-0.38	-1.21	-1.49	-1.34	-1.22	-0.95	-0.56	1.03	1.60	1.59
SMART	1.58	0.55	-0.45	-1.31	-1.59	-1.43	-1.31	-1.04	-0.64	0.95	1.51	1.52
LEAF	1.61	0.59	-0.42	-1.30	-1.59	-1.43	-1.31	-1.04	-0.60	0.98	1.56	1.55
TESLA75	2.03	1.02	-0.01	-0.88	-1.17	-1.01	-0.89	-0.62	-0.18	1.41	2.01	1.97
TESLA100	2.10	1.08	0.06	-0.83	-1.12	-0.95	-0.83	-0.57	-0.12	1.47	2.05	2.04

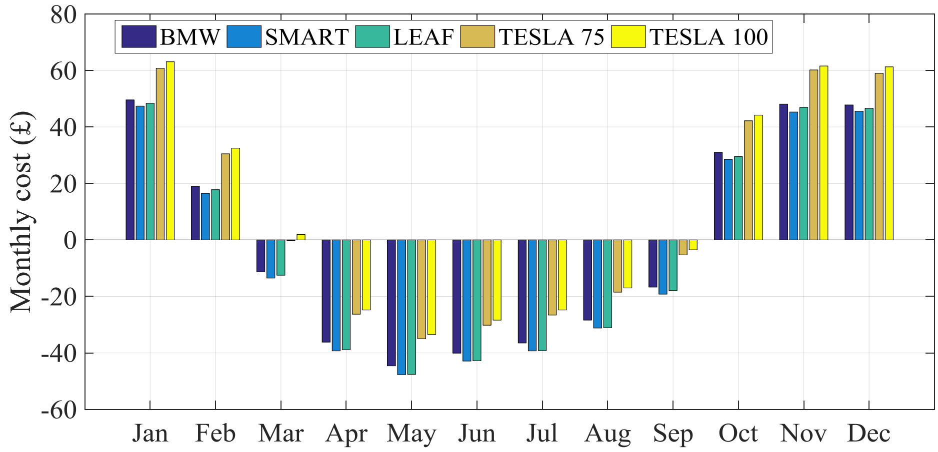

Fig. 6 - 8 Energy consumption cost for different months under TOU tariff after optimisation

Table. 6 - 11 Smart Home Annual energy consumption costs with different EVs after optimisation (£)

Tariff	TESLA100	TESLA75	BMW I3	SMART	LEAF
Fixed tariff	354.8	330.0	192.5	168.6	178.4
TOU tariff	132.5	110.7	-18.1	-49.8	-40.6

Comparing the annual cost of SMART to other EVs under different electricity tariffs, the annual cost of SMART is still the lowest. It can be stated that SMART is currently the most economical EV from energy saving point of view.

6.3.4 Financial analysis of the smart home system without/with optimised control

6.3.4.1 Calculation of the annual cost savings C_s

Two methods of return-of-investment, PB and NPV, have been applied to investigate the economic benefits of the smart home energy system. The methods have been presented in Section 6.1. The annual cost savings C_s in each subsequent year after the initial investment are calculated through (6.6). The data of cash flows for the calculations, such as $C_{non-opt}$ and C_{opt} are sourced from the case studies in subsection 6.3.2 and 6.3.3. Table. 6 - 12 shows the annual cost savings for different EV models under the fixed and TOU tariffs. It can be seen that the annual cost savings are much higher after optimisation, and SMART is still the most economic option for the end user compared to other types of EVs.

Table. 6 - 12 Smart home annual cost savings, C_s, under fixed and TOU tariffs (£)

Brand	TESLA S100	TESLA S75	BMW I3	SMART	LEAF
Without optimisation (fixed tariff)	1,582	1,686	1,882	1,903	1,855
With optimisation (fixed tariff)	2,118	2,142	2,280	2,303	2,293
Without optimisation (TOU tariff)	1,807	1,900	2,053	2,088	2,068
With optimisation (TOU tariff)	2,296	2,318	2,446	2,478	2,469

6.3.4.2 Calculation of maintenance fees, installation cost and OPF

For the smart home system, the main annual maintenance fees come from the costs of maintaining PV system. According to[138], one component of PV system needs to be changed over the lifespan is the inverter, which converts the DC output of PV panel into the AC required by local grids, and the average cost of an inverter is about £1,000. The inverter is assumed to be changed once during total PV lifespan. Furthermore, the solar panels need to be cleaned about every six months when they are contaminated by dirt, debris and pollution. This service, which is done by specialist, usually costs more than £50 quoted from [139]. According to [139], most manufactures offer the 25-year standard solar panel warranty, so the total PV lifespan is selected as 25 years in this work. Table. 6 - 13 shows the annual maintenance costs for PV system.

Table. 6 - 13 Annual maintenance costs, C_m, for PV system

PV lifespan	Annual Inverter cost (£)	Annual maintenance cost (£)	Annual total costs (£)
25 years	40	100	140

The annual operating cash flow, OPF, after the first initial investment of the smart home can be calculated through (6.5). The data of C_s and C_m are sourced from Table. 6 - 12 and Table. 6 - 13. Results of OPF for different types of EV are shown in the following table.

Table. 6 - 14 Annual operating cash flow, OPF , (£)

EV	Tesla S100	Tesla S75	BMW I3	SMART	LEAF
With optimisation (fixed tariff)	1,442	1,546	1,742	1,763	1,715
Without optimisation (fixed tariff)	1,667	1,760	1,913	1,948	1,928
With optimisation (TOU tariff)	1,978	2,002	2,140	2,163	2,153
Without optimisation (TOU tariff)	2,156	2,178	2,306	2,338	2,329

The initial investment of smart home system is mainly from the installation costs of the whole smart home system. According to (6.8), the installation costs are the costs of installing PV, ESS, EV home charging system, and smart home control system. Table. 6 - 15 shows the initial investment for setting up a smart home system built in Chapter 5. The data are sourced from [113, 140-142]. The total initial investment of smart home system with 4kW PV system and one pack of Tesla Powerwall, C_I , will be £10,148.

Table. 6 - 15 Initial investment for a smart home system

Equipment	PV	ESS	EV charging device	Smart home system
Installation cost (£)	1,505/kW	2,300/pack	647	1,181

6.3.4.3 Payback periods and NPV for smart home systems

According to (6.9), the payback period for different types of EVs can be obtained as shown in Table. 6 - 16.

Table. 6 - 16 Payback period of the residential system for different types of EV (years)

EV Models	PB w/o optimisation (fixed tariff)	PB w/o optimisation (TOU tariff)	PB with optimisation (fixed tariff)	PB with optimisation (TOU tariff)
BMW I3	5.80	5.30	4.70	4.40
SMART	5.80	5.20	4.70	4.30
LEAF	5.90	5.30	4.70	4.40
TESLA 75	6.60	5.80	5.10	4.70
TESLA 100	7.00	6.10	5.10	4.70
Average	6.22	5.54	4.86	4.50

According to Table. 6 - 16, it can be concluded that the payback period is longer if the price of EV is higher but its efficiency is lower; however, the payback period can be significantly reduced through optimised DSM. The overall payback period of the smart home system under the optimised control is always shorter compared to the system without optimisation.

The preliminary analysis on return-of-investment has been performed using the payback period method. Next the TVM index, expressed in (6.3), is applied for complementary analysis in DPB. In this case, the discounted rate is selected as 2.4% which is same with the inflation rate in UK [143]. The cash inflow value factor, the discounted cash inflow, and the cumulative discounted cash inflow for different EV can be calculated as shown from Appendix, Table B. 1 ~Table B. 20. Table. 6 - 17 shows the payback period after discounting the cash flow.

Table. 6 - 17 Payback period (DPB) for different types of EV after discounting the cash flow (years)

EV	w/o optimisation (fixed tariff)	w/o optimisation ((TOU tariff)	with optimisation (fixed tariff)	with optimisation (TOU tariff)
BMW I3	6.35	5.74	5.10	4.71
SMART	6.27	5.63	5.04	4.64
LEAF	6.46	5.69	5.06	4.66
TESLA 75	7.23	6.28	5.47	5.00
TESLA 100	7.80	6.66	5.54	5.06
Average DPB	6.82	6.00	5.24	4.81

As can been seen from Table. 6 - 17, the payback period after discounting the cash flow is longer than the case without considering the discounted cash flow. The averaged discounted payback periods are also shown in Table. 6 - 17. The EV that can achieve the lowest DPB to match the initial cash outlay is still the SMART after discounted the cash flow.

Assuming that the time required for the initial investment return of the smart home system is the averaged DPB. If they are not integer number, we will round it up to the nearest integer, e.g. if DPB is 6.35 years, then we select 7 years as the time of return-of-investment. In order to analyse whether the selected EV can achieve profitability on expected year of recovering the investment, the NPV method is applied to further analyse the profitability of the investment. According to [132], a positive NPV on the expected year of recovering the investment denotes that the earnings generated by the project exceeds the initial costs, which can be accepted by the users. On the other hand, the investment with a negative NPV should be rejected by the users. Table. 6 - 18 shows the results of NPV under different cases.

Table. 6 - 18 Results of NPV signal for different cases

EV	NPV signal w/o optimisation (fixed tariff)	NPV w/o optimisation (TOU tariff)	NPV with optimisation (fixed tariff)	NPV with optimisation (TOU tariff)
BMW I3	+	+	+	+
SMART	+	+	+	+
LEAF	+	+	+	+
TESLA 75	-	-	-	-
TESLA 100	-	-	-	-

It can be seen from Table. 6 - 18, three types of EV, which are BMW i3, SMART, and LEAF, are acceptable for the users either with or without optimal control, if the time required for the investment return of the smart system is selected following the above assumption. For TESLA 75 and TESLA 100, the relevant NPVs are negative either for fixed tariff or TOU tariff. The main reason is because of their battery packs are much higher than other EVs, so the battery degradation costs are much higher. End user has to spend longer time to return the initial investment.

6.3.5 Financial analysis of the residential home system including SWH

The above analyses calculates the payback period of the smart home system, which includes PV, ESS, and EV, either with optimal control or without optimal control. The results show that if users select the SMART EV, then the initial investment can be returned quicker than other types of EVs under both the fixed and the TOU electricity tariffs. In this section, another controllable device, the solar thermal water heater, has been added into the smart home energy system. Two different solar thermal systems are compared, the PV-SWH system and the PV-T system. Only the fixed tariff has been applied. The split areas for PV-SWH is selected from the result in 5.4.4 The same three methods, PB, DPB and NPV, are applied to investigate the return-of-investment.

Table. 6 - 19 shows the average daily cost for different months when the SWH is used (the selected EV is SMART). Comparing Table. 6 – 19 with Table. 6 - 9, it can be seen that the daily energy cost has been successfully reduced with the use of SWH, which is mainly resulted from energy savings of the hot water consumption. In addition, it can be observed that larger volume of water tank will reduce the user's daily cost further. However, if the volume of tank is too large for the end user who has a relatively lower daily hot water demand, then the cost reduction will be decreased. Also, the purchase cost of larger volume tank is higher. In the following annual cost analysis, a tank with the volume of 160L is considered for SWH. This tank size can sufficiently guarantee the daily hot water consumption for a household up to three people [144]. Table. 6 - 20 and Table. 6 – 21 show the minimum costs for different type of EVs with PV-SWH system and PV-T system, respectively.

Table. 6 - 19 Daily energy consumption cost (£) of different months for different volumes of SWH

Volume (L)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
80	1.67	0.70	-0.23	-1.03	-1.24	-1.11	-1.03	-0.82	-0.44	1.10	1.63	1.71
120	1.57	0.65	-0.27	-1.06	-1.29	-1.16	-1.07	-0.85	-0.47	1.07	1.56	1.61
160	1.47	0.60	-0.30	-1.11	-1.34	-1.23	-1.13	-0.89	-0.50	1.00	1.49	1.51
200	1.46	0.59	-0.33	-1.14	-1.38	-1.28	-1.18	-0.94	-0.55	0.95	1.47	1.51
240	1.45	0.53	-0.39	-1.21	-1.42	-1.31	-1.25	-0.99	-0.59	0.91	1.42	0.70

Table. 6 - 20 Daily energy consumption cost (£) for different type of EVs with 160L of SWH

EV Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SMART	1.47	0.60	-0.30	-1.11	-1.34	-1.23	-1.13	-0.89	-0.50	1.00	1.49	1.51
BMW I3	1.53	0.67	-0.25	-1.10	-1.25	-1.16	-1.05	-0.81	-0.44	1.06	1.56	1.56
LEAF	1.51	0.64	-0.27	-1.10	-1.34	-1.23	-1.13	-0.89	-0.46	1.03	1.54	1.55
TESLA 75	1.93	1.06	0.14	-0.68	-0.92	-0.81	-0.71	-0.47	-0.04	1.45	1.98	1.96
TESLA 100	1.98	1.01	0.15	-0.67	-0.88	-0.80	-0.69	-0.45	0.02	1.50	2.07	2.05

Table. 6 - 21 Daily energy consumption cost (£) for different type of EVs with 160L of PV-T

EV Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SMART	1.17	0.06	-1.18	-2.51	-3.04	-2.73	-2.50	-2.03	-1.45	0.44	1.08	1.15
BMW I3	1.23	0.13	-1.13	-2.50	-2.95	-2.66	-2.42	-1.95	-1.39	0.50	1.15	1.20
LEAF	1.21	0.10	-1.15	-2.50	-3.00	-2.70	-2.45	-2.00	-1.41	0.47	1.13	1.19

TESLA 75	1.63	0.52	-0.74	-2.08	-2.62	-2.31	-2.08	-1.61	-0.99	0.89	1.57	1.60
TESLA 100	1.68	0.47	-0.73	-2.07	-2.58	-2.3	-2.06	-1.59	-0.93	0.94	1.66	1.69

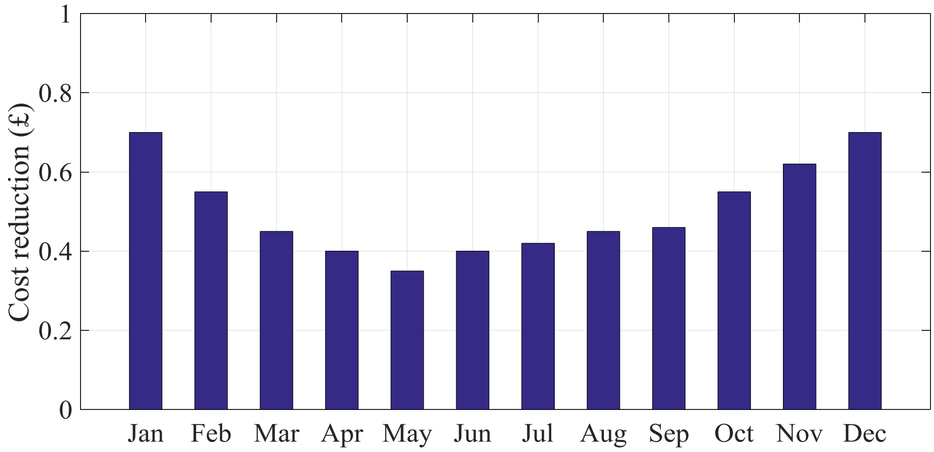

Fig. 6 - 9 Cost reduction of different months with SWH

The annual costs for PV-SWH, PV-T are shown in Table. 6 - 22. Regardless of EV types, the cost has been significantly reduced with the use of solar energy supply. The cost reduction varies from one month to another, which is the difference between Table. 6 - 9 and Table. 6 - 20 . Fig. 6 - 9 shows the cost reductions at different months. It can be seen that the cost reductions are higher during the winter season, and lower during the summer season. This is because of the area of SWH is selected to be sufficient for winter case, which is 30% of total area from subsection 5.4.4, and it is too large for summer time.

In addition, PV is included in non-SWH system, which can also help to reduce the total cost. If the system includes SWH, larger area of SWH means less area of PV is installed. Therefore, higher solar irradiance will result in lower cost reduction. Furthermore, the inlet water temperature during the summer season, which is 15℃, is higher than the winter season (8℃), so less solar irradiance for heating the water is needed. In summary, the benefits of SWH during the summer season are less than the winter season from the economic point of view.

Table. 6 - 22 Annual cost comparison between PV-SWH and PV-T (£)

EV Models	Annual cost with PV-SWH	Annual cost with PV-T	Annual cost without SWH
SMART	-13.78	-350.40	192.5
BMW I3	9.05	-324.85	168.6

LEAF	-5.32	-335.80	178.4
TESLA75	147.96	-186.15	330.0
TESLA100	156.22	-177.02	354.8

With the above results, the optimized daily cost of the smart home can be calculated including SWH, as shown in Table. 6 - 20. It's reported in [145] that the maintenance costs of SWH are very low, and most SWH systems come with up to 10 years warranty and require little maintenance. Thus the annual maintenance costs of SWH are ignored in this case, and the annual operation and maintenance of the smart home system are the same as Section 6.3.4. Therefore, the OPF for different types of EVs can be calculated, and the results are shown in Table. 6 - 23.

Table. 6 - 23 OPF for different types of EVs with PV-SWH

EV Models	OPF with PV-SWH (£)	OPF with PV-T (£)
SMART	2,346.08	2,682.70
BMW I3	2,323.25	2,657.20
LEAF	2,337.62	2,668.10
TESLA75	2,184.34	2,518.50
TESLA100	2,175.65	2,508.90

The initial investment of smart home system is mainly from the installation costs of the whole smart home system. In this case, the SWH has been included, so the cost of installing SWH should be added into the total installation costs. According to [146], the cost of a typical SWH system is around £500. In addition, if SWH system is installed, the area for installing PV panel will be decreased, so the PV system is decreased to 2kW. Therefore, initial investment for setting a smart home system with a 2kW PV system, one pack of Tesla Powerwall and a typical SWH system will be £7,638, which is calculated from the data in Table. 6 - 15. If a PV-T system is applied, the total roof area can be utilised for the solar panel. In this case, it is assumed that the electricity output part of PV-T can be increased to 3kW. According to [147], the PV-T installation cost is 10% higher than the traditional PV system, so the relevant cost will be 1,505*3*110%=£4,966. The overall cost of the smart home system will be £9,094. According to (6.1), the payback periods for PV-SWH and PV-T system can be obtained as shown in Table. 6 - 24.

Table. 6 - 24 Comparison of PB and DPB for PV-SWH and PV-T (years)

EV Models	PB of PV-SWH	PB of PV-T	DPB of PV-SWH	DPB for PV-T
BMW I3	3.30	3.39	3.47	3.67
SMART	3.33	3.42	3.43	3.58
LEAF	3.31	3.41	3.44	3.60
TESLA75	3.54	3.61	3.70	3.82
TESLA100	3.56	3.62	3.71	3.84

As can be seen from the Table. 6 - 24, the payback period of the whole smart home systems are decreased when the PV-SWH or PV-T is included. One reason is that the size of PV system is decreased, which cause the decrease of the initial costs. Another reason is that the solar thermal collector can help to reduce the energy cost, and the installation costs of a PV-SWH system or PV-T system are not very high. Furthermore, results show that the payback periods are shorter if the selected hybrid PV solar thermal system is PV-SWH system. Table. 6 - 24 also shows the results when the discounted rate is included in the calculation of payback-period, and the DPB is shorter if the solar thermal system is included compared to non-thermal system.

According to the results of Table. 6 - 22, the annual cost can be decreased if the solar thermal system is included in the smart home system. Next, the NPV method is applied for further analysis. The lifetime of SWH is selected as 10 years according to [148]. In this study, cash inflows of 9 years are calculated for both PV-SWH and PV-T systems, which are shown in Appendix. B. The index of NPV, which indicates whether the investment should be accepted, is obtained as shown in Table. 6 - 25. In this case, all NPV values are positive, which means the cost savings generated by the smart home system exceeds the initial cost on the expected year with all selected EVs, and the system with the solar thermal system can be accepted. When comparing the cash inflows of 9 years periods between PV-SWH and PV-T systems, as shown by Table. 6 - 26, the profits of the smart home system will be higher for the PV-T option. For this reason, the hybrid PV-T system can be recommended for the end user from long term perspective of the investment.

Table. 6 - 25 NPV signal of the residential system including SWH

EV Models	NPV for PV-SWH	NPV for PV-T
BMW I3	+	+

SMART	+	+
LEAF	+	+
Tesla 75	+	+
Tesla 100	+	+

Table. 6 - 26 9 years cumulative discounted cash flow for PV-T and PV-SWH systems

EV Models	PV-T system (£)	PV-SWH system (£)
BMW I3	12,185	10,966
SMART	12,393	11,150
LEAF	12,273	11,086
Tesla 75	11,080	9,853
Tesla 100	11,000	9,789

6.4 Summary

In this chapter, three appraisal methods, PB, DPB and NPV, have been applied to analyse the investment worth of the residential home energy system. In the case study, the solar radiation levels at different months are considered to calculate the average daily costs in each month, based on which the annual cost savings can be calculated. Three different residential systems have been investigated, which are the traditional household energy system, the smart home energy system without optimisation, and the optimised smart home energy system. The energy costs of these three systems have been calculated. The financial analysis shows that the end user can achieve more economic benefits from smart homes compared to the traditional residential home system. Comparing the non-optimised smart home system with the optimised system, it can be concluded that the optimisation scheme can help to reduce the payback period. Case study results show that, for a typical smart home setting with EV, the average optimised payback period is 4.7 years which is 1.2 years shorter than the non-optimised system. In addition to PB, the DPB method is applied to avoid the TVM problem; the discounted payback period for optimised and non-optimised smart home systems are compared. Furthermore, the NPV analysis is applied and the results suggest that three types of EVs can be accepted by the end users, which are SMART, BMW, and LEAF.

Financial analysis has also been made to compare the PV-SWH system and the PV-T system. The NPV analysis result indicate that both systems can be accepted for all types of EVs. The average payback period of the smart home system with solar thermal collectors (either PV-SWH or PV-T), will be much short than the home without thermal collectors. In addition, the uncertainty of findings in Chapter 6 are mainly resulted from two aspects. One is the initial investment of the smart home system which is fixed type, such as EV battery pack purchase costs, PV panel costs, energy system costs and maintenance costs. The other one is the factor that influence the results calculated from the mathematical model, which is unfixed type, such as electricity tariff, different initial values and driving probabilities.

Chapter 7 Conclusions

7.1 Conclusions

Traditional power grids face barriers and challenges when synchronising large scale renewable generation due to the intermittent characteristics of these resources. In order to address these issues related to grid connection, ESS can be used to store energy for future needs and thus relieve the adverse impact of renewable generation. A popular energy storage device is battery pack, which is also the core part of an EV. In fact, an EV can be used as the storage energy device that is able to inject the stored electric power back to the grid, which is called V2G. This can be applied as a new type of energy source and utilised together with ESS in order to achieve optimal operation of power systems.

With the development of these new technologies, the traditional grids need to be upgraded into smart grid that can help to manage the variability of renewable resources and intelligently interact with all users connected to the grid. More importantly, end users will attribute to energy management in smart grid systems in the future; therefore, DSM is required to influence the load, and help to promote the utilisation of renewable resources for the end users. In DSM, customers play an important role as they have the choice from a range of products according to their preference. For residential home users, a household energy management system can benefit the customers and encourage them to participate in V2G.

As EVs have become more and more popular for residential users, reducing the charging cost of EVs is crucial to attract more end users to participate DSM schemes or other energy policies. For this reason, optimised charging control of EVs, which aims at cost reduction for users, should be investigated. In addition, with V2G involved, the energy cost of the end user could be further reduced when ESS is utilised together. However, there is an issue in applying V2G, which is economic viability of V2G due to the high discharging cost. This is often related to factors such as battery degradation, expensive battery pack and low FIT. Furthermore, when EV is considered into the cost minimisation model of end users, the customer's driving behaviours are also affect implementation of DSM programmes, and will certainly influence the cost reductions and the charging and discharging control of EVs for the household energy management.

When solar energy supply is provided to a residential home, PV and SWH systems are two established technologies. The SWH back-up electricity system can be controlled following the switching on-off characteristics.

To achieve DSM optimisation for smart home systems, initial investments on PV, SWH and ESS, cannot be ignored. Whether the cost savings calculated from the optimisation can compensate the investments needs to be examined.

In this thesis, a mathematical model is built for a residential energy system consisting of an EV, an ESS, renewable generation (PV), and other residential loads. The end user's driving behaviours are considered in this model with the probabilities calculated from survey data. The main objective of this model is to minimise the cost of end user by controlling charging/discharging status of EV and ESS. The relevant battery degradation cost due to V2G are also considered in the optimisation, and whether the existing export tariff is profitable for V2G application has been revealed through case studies. Furthermore, this model can be conveniently expanded to include more controllable components. Two hybrid solar thermal systems, PV-SWH and PV-T, are considered and compared. The benefits of solar thermal system for the end user are investigated from the economic point of view. The split of the limited solar panel area between SWH and PV is determined when other DSM factors are optimised together under the same modelling framework. Finally, different appraisal methods are applied to analyse the investment worth of the residential systems. Comparisons of different household systems and the optimal system choices are given, such as EV selection, indications of the installing costs and so on. The input data are assumed to be fixed in the case studies, so the results calculated from the mathematical model would be influenced by different input data, such as electricity tariff, different initial values and driving probabilities. However, the mathematical model built in this study can be easily applied with different input data, and the results can also indicate a helpful guidance for the end user under different situation.

In the case studies, the original input data are sourced from different companies in U.K, such as electricity tariffs, FIT, battery prices of different EVs. Other residential daily load consumption and solar radiation are also selected as the original input data which are assumed to be fixed on each sampling time. With use of selected input data, results of case studies show that the total operational cost remains at the same minimum value if the initial SOC value is larger than or equal to the lower bound of the terminal SOC from the previous driving. This is because of the existing export tariff in U.K is not large enough to compensate for the degradation cost of battery's discharging, and thus, there is no power return either from ESS to home supply or from EV to grid through V2G. The overall cost measure will increase when the initial SOC is smaller than the lower bound of the terminal SOC, and it will be slightly smaller if charging the same amount of energy to EV from a lower initial SOC. Several different EV models are studied, and the economical choice has been provided. Different impacts of the export tariff are discussed. The results show that the EV will only start to discharge when the export tariff is larger than or equal to £0.25/kWh for the fixed tariff, and £0.15/kWh for the TOU tariff in the case studies. These thresholds could be decreased if the battery degradation cost can be decreased in the future. In comparison to the non-optimised typical operation without the optimal DSM, it is found that the proposed optimal solution can achieve cost savings from 9% to 15% under the selected fixed tariff, and from 18% to 48% under the given TOU tariff.

When SWH is included in this residential energy system, the sufficient areas of solar thermal collector for different seasons are obtained. Comparing SWH with PV, the results also show that SWH is necessary to achieve the best economic benefit for the end user and the trade-off decision for different area of SWH and PV are obtained. The factors that influence the water temperature are also investigated. Moreover, the hybrid PV-T system is compared to the hybrid system of PV and SWH. Results show that PV-T system can achieve more cost savings than a combination of PV and SWH. The cost which is obtained through the optimisation have been compared with the non-optimised settings, and the results show that the optimisation can reduce the cost at least 77%.

Finally, several appraisal methods are applied to assess and analyse the investment worth of the residential energy system under the developed optimisation. Results show that the smart home's end user can achieve more economic benefits compared to the traditional residential home system. Comparing the results of non-optimised residential home system to optimised systems, it can be concluded that the optimised DSM can help to reduce the payback period. In addition, the average payback period after the optimisation is 4.7 years which is 1.2 years shorter than the non-optimised situation. If the discounted rate is introduced to discount the cash flow in order to avoid the problem of TVM, the average discounted payback period are 5.0 years and 6.4 years for optimised and non-optimised solutions, respectively. Furthermore, the results of NPV signal for different scenarios indicate that three types of EV are more likely to be accepted by the end users, which are SMART, BMW, and LEAF. The economic benefits of renewable devices, which are PV-SWH and PV-T, are analysed through the above appraisal methods. The NPV analysis indicates that both of PV-SWH and PV-T can be accepted for all types of EVs, and the average payback period of residential system will be much shorter than the system without the solar thermal system. This is mainly resulted from the energy savings from the hot water consumption. Though the payback period of PV-SWH system is shorter than PV-T system, PV-T system is still recommended if the user wants to achieve more benefits from a long term perspective.

7.2 Future perspectives

The works presented in this thesis proposed a novel DSM model framework for a residential home system, considering EV, energy storage system (ESS), renewable technologies, solar thermal technologies and human behaviours. In the light of the direction that this work took, the following research avenues may be of interest to both academia and industry:

- The main objective of this work is to minimise the energy cost of end user for a single residential household system. In the future research, the household system will be expanded to a residential building size system with distribution network, such as commercial building, hospital and so on. Multiple EVs and end users will be considered where they can be jointly managed through the optimisation scheme. The benefits for both sides of end users and grid operator will be investigated. Larger size of PV system and SWH system will be considered.
- The ESS applied in this study is for a single household, which is a small battery based storage. For larger systems, fuel cells can be used as a back-up power system. It can also be implemented as part of the combined heat and power

(CHP) system, where the thermal energy from the fuel cell exhaustion is recovered and used to heat or cool residential buildings. Therefore, a CHP system will be established by considering renewable generation, fuel cell, for a residential building. The investment worth of the residential building energy system will also be analysed through the appraisal methods.

- The driving behaviours of the end user are described through a practical survey. It can describe a single user's driving behaviours but may not suitable for multiple end users. In a residential building, the end users' vehicles are parked in a building car park. A typical car park traffic flow model will be added to describe the driving behaviours for the residential building.

Appendix

A. Survey Data

The survey was conducted by designed questionnaires and there were 201 respondents participated, each with a full time job, a driving license and aged between 22 to 55 years old. The area Most of them responded the survey through online service, and the time period for this survey was between Oct 2016 and Jan 2017. The averaged probabilities from the 201 questionnaires are summarised in the tables below, in which all the figures are normalised in percentage.

Table A. 1 Purpose of driving and probabilities

Purpose of driving	Probability (%)
a. Shopping	20.96
b. Dating/Camping/Entertainment (Entertain.)	25.55
c. Go to work/meeting (Business)	23.95
d. Pick up friends/children	16.97
e. Travel for other purposes (Others)	12.57

Table A. 2 Driving distance (normalised in percentage for each row)

Driving distance, miles	< 1	1-3	3-5	5-10	10-20	20-40	40-80	80-120	120-160	160-200	> 200
a. Shopping	28.14	46.71	14.37	6.59	2.99	0.00	1.20	0.00	0.00	0.00	0.00
b. Entertain.	4.19	14.97	21.56	17.96	14.97	14.97	5.99	3.59	1.20	0.00	0.60
c. Business	4.79	19.16	21.56	25.75	13.17	6.59	7.78	0.60	0.00	0.60	0.00
d. Pick up	10.78	25.75	28.14	17.96	9.58	4.79	2.40	0.60	0.00	0.00	0.00
e. Others	4.79	0.60	4.19	2.40	5.39	2.40	11.98	26.35	5.99	7.78	28.14

Table A. 3 Driving time period (normalised in percentage for each row)

Driving time period	7:00-10:00	10:00-14:00	14:00-17:00	17:00-20:00	20:00-23:00	After23:00
a. Shopping	15.09	11.20	15.09	44.79	13.83	0.00
b. Entertain.	11.47	17.93	18.65	28.68	18.61	4.66
c. Business	49.71	15.44	14.31	17.53	2.26	0.75
d. Pick up	37.18	8.61	11.35	32.79	6.65	3.42

e. Others	32.22	25.71	15.95	12.00	7.61	6.51

Table A. 4 Driving time duration (normalised in percentage for each row)

Driving time duration	< 10 mins	10 -20 mins	20 -30 mins	30 mins-1 hr	1 - 2 hrs	2 -3 hrs	4 hrs
a. Shopping	34.73	43.71	13.77	7.19	0.60	0	0
b. Entertainment	4.19	11.38	23.35	29.34	15.57	7.79	8.38
c. Business	7.78	28.14	26.35	21.56	8.39	3.59	4.19
d. Pick up	9.58	37.13	22.16	20.36	7.77	1.80	1.20
e. Others	2.99	1.20	1.20	2.40	12.57	13.77	65.87

Table A. 5 Parking time duration (normalised in percentage for each row)

Parking time duration	< 10 mins	10 -20 mins	20 -30 mins	30mins-1 hr	1 - 2 hrs	2 -3 hrs	4 hrs	6 hrs
a. Shopping	6.59	10.78	15.57	37.13	20.36	7.19	2.38	0
b. Entertainment	4.19	2.99	4.19	4.79	25.75	34.13	13.78	10.18
c. Business	4.79	3.59	4.79	4.19	13.17	11.38	16.17	41.92
d. Pick up	28.95	31.34	20.56	4.19	5.99	5.39	1.78	1.80
e. Others	5.99	4.19	1.20	2.99	4.79	4.79	10.18	65.87

B. Annual cash flow and cumulative cash flow for different cases

Table B. 1 BMW annual cash flow and cumulative cash flow without optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,742	0.9766	1,701	-8,447
2	1,742	0.9537	1,661	-6,785
3	1,742	0.9313	1,622	-5,163
4	1,742	0.9095	1,584	-3,579
5	1,742	0.8882	1,547	-2,031
6	1,742	0.8674	1,511	-520
7	1,742	0.8470	1,475	955
8	1,742	0.8272	1,441	2,396
9	1,742	0.8078	1,407	3,803

Table B. 2 SMART annual cash flow and cumulative cash flow without optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,763	0.9766	1,722	-8,426
2	1,763	0.9537	1,681	-6,745
3	1,763	0.9313	1,642	-5,103
4	1,763	0.9095	1,603	-3,500
5	1,763	0.8882	1,566	-1,934
6	1,763	0.8674	1,529	-404
7	1,763	0.8470	1,493	1,089
8	1,763	0.8272	1,458	2,547
9	1,763	0.8078	1,424	3,971

Table B. 3 LEAF annual cash flow and cumulative cash flow without optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,715	0.9766	1,675	-8,473
2	1,715	0.9537	1,636	-6,838
3	1,715	0.9313	1,597	-5,240
4	1,715	0.9095	1,560	-3,681
5	1,715	0.8882	1,523	-2,157
6	1,715	0.8674	1,488	-670
7	1,715	0.8470	1,453	783
8	1,715	0.8272	1,419	2,202
9	1,715	0.8078	1,385	3,587

Table B. 4 TESLA 75 annual cash flow and cumulative cash flow without optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,546	0.9766	1,510	-8,638
2	1,546	0.9537	1,474	-7,164

3	1,546	0.9313	1,440	-5,724
4	1,546	0.9095	1,406	-4,318
5	1,546	0.8882	1,373	-2,945
6	1,546	0.8674	1,341	-1,604
7	1,546	0.8470	1,309	-294
8	1,546	0.8272	1,279	985
9	1,546	0.8078	1,249	2,233

Table B. 5 TESLA 100 annual cash flow and cumulative cash flow without optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,442	0.9766	1,408	-8,740
2	1,442	0.9537	1,375	-7,365
3	1,442	0.9313	1,343	-6,022
4	1,442	0.9095	1,311	-4,710
5	1,442	0.8882	1,281	-3,429
6	1,442	0.8674	1,251	-2,178
7	1,442	0.8470	1,221	-957
8	1,442	0.8272	1,193	236
9	1,442	0.8078	1,165	1,401

Table B. 6 BMW annual cash flow and cumulative cash flow without optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,913	0.9766	1,868	-8,280
2	1,913	0.9537	1,824	-6,455
3	1,913	0.9313	1,782	-4,674
4	1,913	0.9095	1,740	-2,934
5	1,913	0.8882	1,699	-1,235
6	1,913	0.8674	1,659	425
7	1,913	0.8470	1,620	2,045
8	1,913	0.8272	1,582	3,627
9	1,913	0.8078	1,545	5,173

Table B. 7 SMART annual cash flow and cumulative cash flow without optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,948	0.9766	1,902	-8,246
2	1,948	0.9537	1,858	-6,388
3	1,948	0.9313	1,814	-4,574
4	1,948	0.9095	1,772	-2,802
5	1,948	0.8882	1,730	-1,072
6	1,948	0.8674	1,690	618
7	1,948	0.8470	1,650	2,268
8	1,948	0.8272	1,611	3,879
9	1,948	0.8078	1,574	5,453

Table B. 8 LEAF annual cash flow and cumulative cash flow without optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,928	0.9766	1,883	-8,265
2	1,928	0.9537	1,839	-6,426
3	1,928	0.9313	1,796	-4,631
4	1,928	0.9095	1,754	-2,877
5	1,928	0.8882	1,712	-1,165
6	1,928	0.8674	1,672	507
7	1,928	0.8470	1,633	2,140
8	1,928	0.8272	1,595	3,735
9	1,928	0.8078	1,557	5,293

Table B. 9 TESLA 75 annual cash flow and cumulative cash flow without optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,760	0.9766	1,719	-8,429
2	1,760	0.9537	1,679	-6,751

3	1,760	0.9313	1,639	-5,112
4	1,760	0.9095	1,601	-3,511
5	1,760	0.8882	1,563	-1,948
6	1,760	0.8674	1,527	-421
7	1,760	0.8470	1,491	1,070
8	1,760	0.8272	1,456	2,526
9	1,760	0.8078	1,422	3,947

Table B. 10 TESLA 100 annual cash flow and cumulative cash flow without optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,667	0.9766	1,628	-8,520
2	1,667	0.9537	1,590	-6,930
3	1,667	0.9313	1,552	-5,378
4	1,667	0.9095	1,516	-3,862
5	1,667	0.8882	1,481	-2,381
6	1,667	0.8674	1,446	-935
7	1,667	0.8470	1,412	477
8	1,667	0.8272	1,379	1,856
9	1,667	0.8078	1,347	3,203

Table B. 11 BMW annual cash flow and cumulative cash flow after optimisation if electricity tariff is fixed

Year BMW	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,140	0.9766	2,090	-8,058
2	2,140	0.9537	2,041	-6,017
3	2,140	0.9313	1,993	-4,024
4	2,140	0.9095	1,946	-2,078
5	2,140	0.8882	1,901	-177
6	2,140	0.8674	1,856	1,679
7	2,140	0.8470	1,813	3,492
8	2,140	0.8272	1,770	5,262
9	2,140	0.8078	1,729	6,991

Table B. 12 SMART annual cash flow and cumulative cash flow after optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,163	0.9766	2,112	-8,036
2	2,163	0.9537	2,063	-5,973
3	2,163	0.9313	2,014	-3,958
4	2,163	0.9095	1,967	-1,991
5	2,163	0.8882	1,921	-70
6	2,163	0.8674	1,876	1,806
7	2,163	0.8470	1,832	3,638
8	2,163	0.8272	1,789	5,428
9	2,163	0.8078	1,747	7,175

Table B. 13 LEAF annual cash flow and cumulative cash flow after optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,153	0.9766	2,103	-8,045
2	2,153	0.9537	2,053	-5,992
3	2,153	0.9313	2,005	-3,987
4	2,153	0.9095	1,958	-2,029
5	2,153	0.8882	1,912	-117
6	2,153	0.8674	1,868	1,751
7	2,153	0.8470	1,824	3,575
8	2,153	0.8272	1,781	5,356
9	2,153	0.8078	1,739	7,095

Table B. 14 TESLA 75 annual cash flow and cumulative cash flow after optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,002	0.9766	1,955	-8,193
2	2,002	0.9537	1,909	-6,284
3	2,002	0.9313	1,864	-4,419

4	2,002	0.9095	1,821	-2,598
5	2,002	0.8882	1,778	-820
6	2,002	0.8674	1,737	916
7	2,002	0.8470	1,696	2,612
8	2,002	0.8272	1,656	4,268
9	2,002	0.8078	1,617	5,885

Table B. 15 TESLA 100 annual cash flow and cumulative cash flow after optimisation if electricity tariff is fixed

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	1,978	0.9766	1,932	-8,216
2	1,978	0.9537	1,886	-6,330
3	1,978	0.9313	1,842	-4,488
4	1,978	0.9095	1,799	-2,689
5	1,978	0.8882	1,757	-932
6	1,978	0.8674	1,716	784
7	1,978	0.8470	1,675	2,459
8	1,978	0.8272	1,636	4,095
9	1,978	0.8078	1,598	5,693

Table B. 16 BMW annual cash flow and cumulative cash flow after optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,306	0.9766	2,252	-7,896
2	2,306	0.9537	2,199	-5,697
3	2,306	0.9313	2,148	-3,549
4	2,306	0.9095	2,097	-1,452
5	2,306	0.8882	2,048	596
6	2,306	0.8674	2,000	2,597
7	2,306	0.8470	1,953	4,550
8	2,306	0.8272	1,908	6,457
9	2,306	0.8078	1,863	8,320

Table B. 17 SMART annual cash flow and cumulative cash flow after optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,338	0.9766	2,283	-7,865
2	2,338	0.9537	2,230	-5,635
3	2,338	0.9313	2,177	-3,458
4	2,338	0.9095	2,126	-1,331
5	2,338	0.8882	2,077	745
6	2,338	0.8674	2,028	2,773
7	2,338	0.8470	1,980	4,754
8	2,338	0.8272	1,934	6,688
9	2,338	0.8078	1,889	8,576

Table B. 18 LEAF annual cash flow and cumulative cash flow after optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,329	0.9766	2,275	-7,873
2	2,329	0.9537	2,221	-5,652
3	2,329	0.9313	2,169	-3,483
4	2,329	0.9095	2,118	-1,365
5	2,329	0.8882	2,069	704
6	2,329	0.8674	2,020	2,724
7	2,329	0.8470	1,973	4,696
8	2,329	0.8272	1,927	6,623
9	2,329	0.8078	1,881	8,504

Table B. 19 TESLA 75 annual cash flow and cumulative cash flow after optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,178	0.9766	2,127	-8,021
2	2,178	0.9537	2,077	-5,944

3	2,178	0.9313	2,028	-3,915
4	2,178	0.9095	1,981	-1,935
5	2,178	0.8882	1,935	0
6	2,178	0.8674	1,889	1,889
7	2,178	0.8470	1,845	3,734
8	2,178	0.8272	1,802	5,536
9	2,178	0.8078	1,759	7,295

Table B. 20 TESLA 100 annual cash flow and cumulative cash flow after optimisation if electricity tariff is TOU

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-10,148	1	-10,148	-10,148
1	2,156	0.9766	2,106	-8,042
2	2,156	0.9537	2,056	-5,986
3	2,156	0.9313	2,008	-3,978
4	2,156	0.9095	1,961	-2,018
5	2,156	0.8882	1,915	-103
6	2,156	0.8674	1,870	1,768
7	2,156	0.8470	1,826	3,594
8	2,156	0.8272	1,783	5,377
9	2,156	0.8078	1,742	7,119

Table B. 21 BMW annual cash flow and cumulative cash flow after optimisation for PV-SWH system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-7,638	1	-7638	-7,638
1	2,323	0.9766	2,269	-5,369
2	2,323	0.9537	2,215	-3,154
3	2,323	0.9313	2,163	-991
4	2,323	0.9095	2,113	1,122
5	2,323	0.8882	2,063	3,186
6	2,323	0.8674	2,015	5,201
7	2,323	0.8470	1,968	7,168
8	2,323	0.8272	1,922	9,090
9	2,323	0.8078	1,877	10,966

Table B. 22 SMART annual cash flow and cumulative cash flow after optimisation for PV-SWH system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-7,638	1	-7638	-7,638
1	2,346	0.9766	2,291	-5,347
2	2,346	0.9537	2,237	-3,110
3	2,346	0.9313	2,185	-925
4	2,346	0.9095	2,134	1,209
5	2,346	0.8882	2,084	3,293
6	2,346	0.8674	2,035	5,328
7	2,346	0.8470	1,987	7,315
8	2,346	0.8272	1,941	9,255
9	2,346	0.8078	1,895	11,150

Table B. 23 LEAF annual cash flow and cumulative cash flow after optimisation for PV-SWH system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-7,638	1	-7638	-7,638
1	2,338	0.9766	2,283	-5,355
2	2,338	0.9537	2,230	-3,125
3	2,338	0.9313	2,177	-948
4	2,338	0.9095	2,126	1,179
5	2,338	0.8882	2,077	3,255
6	2,338	0.8674	2,028	5,283
7	2,338	0.8470	1,980	7,264
8	2,338	0.8272	1,934	9,198
9	2,338	0.8078	1,889	11,086

Table B. 24 TESLA 75 annual cash flow and cumulative cash flow after optimisation for PV-SWH system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-7,638	1	-7638	-7,638
1	2,184	0.9766	2,133	-5,505
2	2,184	0.9537	2,083	-3,422
3	2,184	0.9313	2,034	-1,388
4	2,184	0.9095	1,986	598

5	2,184	0.8882	1,940	2,538
6	2,184	0.8674	1,894	4,432
7	2,184	0.8470	1,850	6,282
8	2,184	0.8272	1,807	8,089
9	2,184	0.8078	1,764	9,853

Table B. 25 TESLA 100 annual cash flow and cumulative cash flow after optimisation for PV-SWH system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-7,638	1	-7638	-7,638
1	2,176	0.9766	2,125	-5,513
2	2,176	0.9537	2,075	-3,438
3	2,176	0.9313	2,027	-1,411
4	2,176	0.9095	1,979	568
5	2,176	0.8882	1,933	2,501
6	2,176	0.8674	1,887	4,388
7	2,176	0.8470	1,843	6,231
8	2,176	0.8272	1,800	8,031
9	2,176	0.8078	1,758	9,789

Table B. 26 BMW annual cash flow and cumulative cash flow after optimisation for PV-T system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-9,094	1	-9,094	-9,094
1	2,657	0.9766	2,595	-6,499
2	2,657	0.9537	2,534	-3,965
3	2,657	0.9313	2,474	-1,491
4	2,657	0.9095	2,417	926
5	2,657	0.8882	2,360	3,286
6	2,657	0.8674	2,305	5,590
7	2,657	0.8470	2,250	7,841
8	2,657	0.8272	2,198	10,039
9	2,657	0.8078	2,146	12,185

Table B. 27 SMART annual cash flow and cumulative cash flow after optimisation for PV-T system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)

0	-9,094	1	-9,094	-9,094
1	2,683	0.9766	2,620	-6,474
2	2,683	0.9537	2,559	-3,915
3	2,683	0.9313	2,499	-1,416
4	2,683	0.9095	2,440	1,024
5	2,683	0.8882	2,383	3,407
6	2,683	0.8674	2,327	5,734
7	2,683	0.8470	2,273	8,007
8	2,683	0.8272	2,219	10,226
9	2,683	0.8078	2,167	12,393

Table B. 28 LEAF annual cash flow and cumulative cash flow after optimisation for PV-T system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-9,094	1	-9,094	-9,094
1	2,668	0.9766	2,606	-6,488
2	2,668	0.9537	2,544	-3,944
3	2,668	0.9313	2,485	-1,459
4	2,668	0.9095	2,427	967
5	2,668	0.8882	2,370	3,337
6	2,668	0.8674	2,314	5,651
7	2,668	0.8470	2,260	7,911
8	2,668	0.8272	2,207	10,118
9	2,668	0.8078	2,155	12,273

Table B. 29 TESLA 75 annual cash flow and cumulative cash flow after optimisation for PV-T system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-9,094	1	-9,094	-9,094
1	2,519	0.9766	2,460	-6,634
2	2,519	0.9537	2,402	-4,232
3	2,519	0.9313	2,346	-1,886
4	2,519	0.9095	2,291	405
5	2,519	0.8882	2,237	2,643
6	2,519	0.8674	2,185	4,828
7	2,519	0.8470	2,134	6,961
8	2,519	0.8272	2,084	9,045

9	2,519	0.8078	2035	11080

Table B. 30 TESLA 100 annual cash flow and cumulative cash flow after optimisation for PV-T system

Year	OPF (£)	Cash inflow factor	Discounted cash flow (£)	Cumulative discounted cash flow (£)
0	-9,094	1	-9,094	-9,094
1	2,509	0.9766	2,450	-6,644
2	2,509	0.9537	2,393	-4,251
3	2,509	0.9313	2,337	-1,914
4	2,509	0.9095	2,282	368
5	2,509	0.8882	2,228	2,596
6	2,509	0.8674	2,176	4,772
7	2,509	0.8470	2,125	6,898
8	2,509	0.8272	2,075	8,973
9	2,509	0.8078	2,027	11,000

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