# Coupling Simulation with Machine Learning for the Development of a Proactive HVAC System in the Manufacturing Sector

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

# Research Outputs

## Published Research Papers

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3. Mawson, V. J and Hughes, B. R, Thermal modelling of manufacturing processes and HVAC systems, ENERGY, vol 204, 2020.

4. Mawson, V. J, and Hughes, B. R, Coupling Simulation with Artificial Neural Networks for the Optimisation of HVAC Controls in Manufacturing Environments: Optimization and Engineering, SDEWES Special issue, 2020.

# Acronyms

| | |
|---|---|
| AES | Applied Energy Sources |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| ASHRAE | American Society of Heating, Refrigerating and Air Conditioning Engineers |
| CDD | Cooling Degree-days |
| CIBSE | Chartered Institution of Building Services Engineers |
| CPS | Cyber-physical Systems |
| CV-RMSE | Coefficient of variation of the root mean square error |
| DES | Discrete Event Simulation |
| DNN | Deep Neural Network |
| ECPS | Energy Cyber-Physical Systems |
| EES | Energy Efficient Scheduling |
| EPE | Embodied Product Energy |
| HVAC | Heating, Ventilation and Cooling |
| IoT | Internet of Things |
| LCA | Life Cycle Assessment |
| LSMLR | Ordinary Least Squares Multiple Linear Regression |
| LSTM | Long Short Term Memory |
| MAE | Mean Average Error |
| MAPE | Mean Absolute Percentage Error |
| MES | Manufacturing Execution System |
| MFC | Manufacturing Controlled |
| MTO | Made To Order |
| MTS | Made To Stock |

| | |
|---|---|
| NMBE | Normalized Mean bias error |
| ORC | Organic Rankine Cycle |
| PMV | Predicted Mean Vote |
| $R^2$ | Coefficient of Determination |
| ReLu | Rectified Linear Unit Function |
| RMSE | Root Mean Square Error |
| RNN | Recurrent Neural Network |
| SCC | Spearman’s Correlation Coefficient |
| SGD | Stochastic Gradient Descent |
| SME | Small Medium Enterprise |
| Tanh | Hyperbolic Tangent |
| TBS | Technical Building Services |
| TCC | Thermal Comfort Controlled |
| VDI | Verein Deutscher Ingenieure |

# Nomenclature

| | |
|---|---|
| A | Area ($m^2$) |
| $c_p$ | Specific heat capacity ($J\ kg{-1}\ K{-1}$) |
| h | Convection eat transfer coefficient ($W\ m^{-2}\ K^{-1}$) |
| i | time interval (s) |
| k | thermal conductivity ($W\ m^{-1}\ K^{-1}$) |
| L | Length (m) |
| $\dot{m}$ | Mass flow rate ($kg\ s{-1}$) |
| N | total number of days in the specified time interval |
| P | Pressure (Pa) |
| Q | Heat flux ($Wm^{-1}$) |
| $\dot{Q}$ | Rate of heat transfer ($W$) |
| R | Thermal resistance ($W{-1}\ m2\ K$) |
| T | Temperature ($K$) |
| U | Thermal transmittance ($W\ m{-2}\ K{-1}$) |
| v | Velocity ($m\ s^{-1}$) |
| V | Infiltration rate ($m^3\ s^{-1}$) |
| X | distance (m) |
| | |
| $\beta$ | Intercept |
| $\varepsilon$ | Emissivity |
| ρ | Density ($kg\ m^{-3}$) |
| σ | Stefan-Boltzmann Constant ($W\ m^{-2}\ K^{-4}$) |

# Abstract

The industrial sector consumes 55% of the world's energy consumption [1]. Following manufacturing processes, the HVAC system is the second largest energy consumer in manufacturing facilities, yet is generally uncounted for and considered an indirect cost to maintain a facility [2]. Any current efforts at reducing energy demand in the manufacturing sector have been focused towards process machines rather than on the manufacturing building as a holistic energy system.

Currently, HVAC systems are reactive, responding to changes to the environment as they happen, based upon requirements for thermal comfort. Manufacturing facility environments however are subject to complex interactions between machine level resources, water, heat and compressed air.

This study questions the suitability of the reactive thermal comfort based HVAC system, and proposes a proactive manufacturing based HVAC control system, utilising predicted optimum HVAC set points.

Through the use of simulation, a holistic analysis of a manufacturing facility was performed, based on building location and layout, building fabrics, weather conditions and manufacturing demand in order to determine the relationship between manufacturing demand and HVAC control. A number of predictive models were analysed for suitability for use in the manufacturing, before being trained on simulation data for the prediction of optimum HVAC set points and corresponding facility indoor conditions.

Simulation was coupled with predictive modelling in order to predict building energy and HVAC energy demand, allowing for the identification of potential future spikes in consumption, followed by subsequent HVAC and manufacturing schedule optimisation, allowing for a 15.1 % reduction in peak energy demand.

Through simulation and predictive modelling, the research has demonstrated the potential energy savings achieved by adopting a proactive HVAC system in the manufacturing sector. Such a methodology achieved 14.1 % energy savings over a 12-month period for an analysed case study environment.

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# Chapter 1- Introduction

Buildings consume 40% of the world's energy [3]. Furthermore, in the UK, heating ventilation and air conditioning (HVAC) within buildings are responsible for half of the country's energy demand, and account for the highest energy end use in the non-residential sector due to inefficient operation and maintenance [4]. In particular, air conditioning is costly, with the cost of cooling for the few days of the year the UK experiences temperatures over 28 °C equating to a full years' worth of heating [5]. HVAC systems are reactive systems, aiming to provide thermal comfort to occupants as well as remove toxic and waste gases from the indoor environment. Outdoor climatic conditions, solar gains, occupant density, building fabrics, building use, condition requirements and internal gains all influence the amount of heat that needs to be added or removed from a space, which requires constant monitoring and control. Such systems are commonly controlled by thermostats and sensors, combatting undesired changes to the environment as and when they happen by altering controls accordingly.

The industrial sector is responsible for 55% of the world's energy consumption [1], with estimates that the industrial sector will remain the largest consumer of energy in 2040. With increased pressure from governments worldwide to reduce $C0_2$ emissions, along with a rising global population and demand for more manufactured goods, efforts towards improving energy conservation and efficiency is increasing.

In manufacturing facilities, the highest energy consumer is related to manufacturing processes followed by the HVAC system [6]. Manufacturing facilities are complex and highly stochastic, with rigid environmental condition requirements to ensure optimum temperature and humidity for product quality, as well as worker safety through ensuring removal of toxic gases. Such environments are subject to complex interactions between machine level resources, water, heat and compressed air with building level HVAC systems, climatic influences, occupant behaviour and building fabrics.

Furthermore, in the industrial sector, approximately 30% of the energy delivered to a manufacturing site is lost as waste heat [2]. Manufacturing workshops are subject to significant heat gains as a result of high energy consuming equipment, and thus hold great potential for heat recovery, utilising high and low grade waste heat for steam generation or for space heating.

Due to the complexity, intense conditions and requirements of industrial environments, the suitability of reactive thermal comfort based HVAC systems is questionable. Consequently, the manufacturing sector would benefit from a HVAC system which anticipates and responds in advance to significant fluctuations in environmental conditions and in accordance to manufacturing demand. Thus, providing an industrial sector specific system suited to providing required air quality and conditions whilst reducing operational costs and providing environmental benefits.

Furthermore, current building analysis involves calculations based on degree-days, a climatic indicator used to assess the impact of weather on the energy consumption of buildings. The use of degree-days requires a base temperature at which the building is thought to require heating or cooling; specified at 15.5 °C [7]. However such a method has been criticised in the past, [8][9], as building use, indoor temperature and heat gains and losses within the building will significantly impact the energy consumption of the building, in addition to climatic conditions. Manufacturing facilities in particular vary drastically in size and use, with large pieces of equipment contributing a significant amount of latent heat to the indoor environment, thus affecting demand of HVAC systems.

Despite this, the Manual of Recommended Practice [10] for industrial environments states that the primary function of heat control ventilation systems is to prevent the illness and discomfort of workers, with controls based on a physiological evaluation of heat stress for occupants rather than control based on industrial processes or workshop use. The use of degree-days as a methodology of building energy analysis is deemed questionable for manufacturing facilities. Conversely, a holistic evaluation of both the building shell and manufacturing processes aside climatic factors would account for any interacting thermal energy flows and provide a more accurate assessment on the demands of a manufacturing facility.

By adopting cost effective energy reduction strategies, industry has the potential to double production value per unit of energy use in 2040 [11]. Furthermore, adopting technology to intelligently control energy use has the potential to reduce energy consumption by 50% as opposed to making operational improvements, which can reduce this by only 10 – 20% [12]. The development of a proactive based manufacturing specific HVAC system avoids the need for costly technological retrofit and implementation of hardware, yet provides an intelligent control based strategy to aid companies in achieving their energy saving potential.

The main focus for manufacturing production managers is predominately output and productivity based, with energy costs generally uncounted for and considered an indirect cost to maintain a facility [2]. Although companies are beginning to identify energy efficiency as a method of reducing production costs, such a focus is predominately on analysis of manufacturing process machines, such as operating times and maintenance status, rather than on the facility as a whole. A cost effective methodology of integrating manufacturing intelligence across an entire production operation does not exist, and business decisions are often made with little and incomplete knowledge of the relationship between products and energy use [13].

Prior to implementation of energy saving strategies, the key to success is the education regarding thermal energy flows and interactions between equipment, occupants, weather, the built environment and building control.

To unlock the energy saving potential in manufacturing facilities, and aid UK based companies in their mission to achieve legally binding net zero greenhouse gas emissions by 2050 [14], this study aims to provide the methodology needed to integrate manufacturing production with building energy analysis. This is coupled with the provision of tools which provide the knowledge required to implement effective energy saving strategies.

In order to mitigate problems associated with high energy demand, energy saving strategies by management includes energy audits and employee training programs as well as the implementation of energy efficient motors, leak prevention and waste recovery systems in boilers [15]. However, such strategies and training programs can be costly, and therefore a common tool of system analysis prior to strategy implementation is the use of simulation.

## 1.1 Simulation

Simulation is a common tool for the analysis of building energy consumption and thermal behaviour. Used for both existing and prospective buildings, it can identify areas of high-energy consumption and subsequently assess alternative control and design strategies according to predefined criteria in both design and retrofit. Similarly, analysis of manufacturing processes and tools is performed using simulation, analysing energy consumption of individual parts, tools or machine processes. However both the building and manufacturing processes are commonly analysed in isolation, due to differences in preferred analytical paradigms.

Building energy modelling is preferably time driven, continuous simulation, where a simulation variable is incremented at set time intervals with computation at each interval. Thus is suited to analysis of energy flows, weather and variables that advance through time. Whereas manufacturing processes are dynamic and thus more suited to discrete event simulation (DES), where computation is conducted at each event in a sequence, regardless of time between events. An example of which may be analysis of queues, decisions or traffic.

The role of building energy software is determination of the buildings thermal envelope, quantifying energy use dependent upon building use, geometry, fabric and location. The tools can provide insight into building energy consumption, $CO_2$ emissions, peak energy demand, renewable energy production for energy performance, occupant comfort, ventilation and HVAC performance.

Currently available software commonly used for analysis of residential, commercial and industrial buildings include EnergyPlus [16], Autodesk Revit [17], IES-VE [18], ESP-r [19], Trnsys [20] and eQuest [21].

In manufacturing process modelling, tools are commonly adopted for risk management analysis, schedule and system enhancement, bottleneck identification and process optimisation through analysis of machining states. Common available softwares include Lanners WITNESS [22], Plant Simulation [23], Arena [24], SIMUL8 [25] and MATLABs Simulink [26]. Traditionally such manufacturing optimisation softwares have not focused on energy use of equipment or building for achieving energy efficiency improvements [27].

The isolation of both manufacturing and building energy flows utilising these software tools does not allow for the holistic analysis of a facility (Figure 1), with models lacking interaction and interdependencies of parameters and equipment, such as influences of machining heat gain on HVAC requirements, or the influence of machining schedules on indoor environmental temperature.

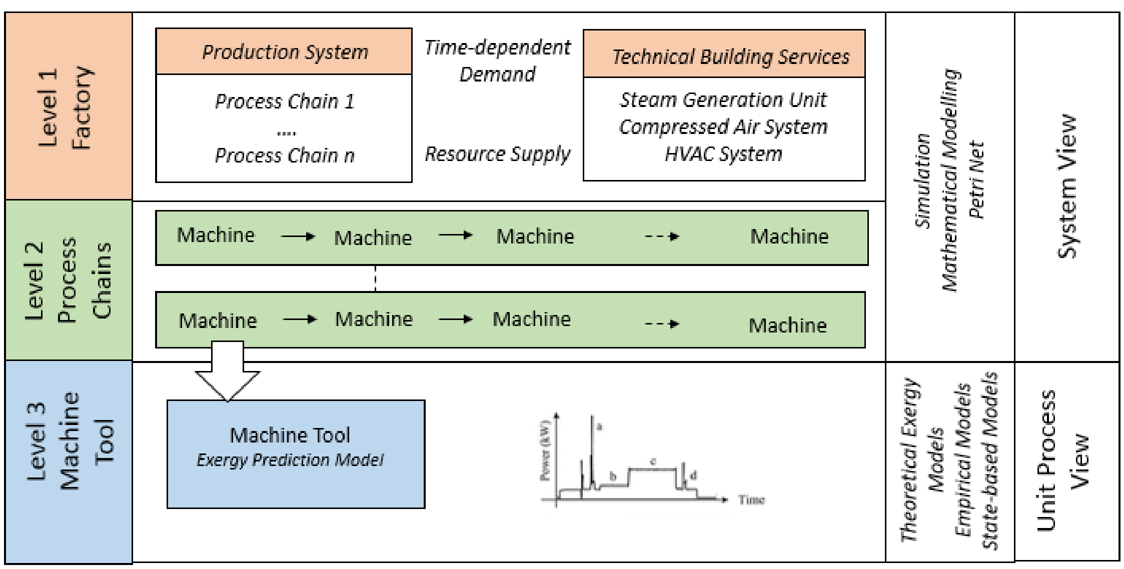



Figure 1- Overview of manufacturing research activities towards energy efficiency (figure reproduced from [32])

Although useful in isolation, combining both approaches allows for analysis on both system and building level asynchonously. As energy is a continous based parameter of which advances through time, adopting the time based tool provides analysis of the system at defined intervals throughout the day. The energy consumption of manufactuirng systems can be analysed similarly, thus allowing for the asynchonous analysis of system and building level.

In order to develop a manufactuirng specific HVAC system, optimum HVAC set points must be determined based upon all interacting thermal energy flows in the facility. Although simulation is an effective tool at system analysis and optomisation, after initial model development, predictive tools (such as machine learning) are subsequently required in order to determine optimum HVAC parameters and avoid the need for time consuming simulation model redevelopment.

## 1.2 Machine Learning

Machine learning tools can be thought of as a form of data analysis which automates analytical model development. Furthermore, models can provide the ability to infer patterns in datasets and observations. Thus, enabling predictions and decisions to be made in new settings and surroundings based on the learnt patterns and relationships. The accuracy of predictions can be constantly improved through experience and exposure to new data.

Machine learning techniques are increasingly being adopted for predictions within the energy and building sector due to their ability to determine complex relationships within a dataset, handling models with a large number of input parameters, yet ignoring excess data of minimal significance to provide conclusions based on key patterns in the data.

Data from the energy and building sector is often noisy and stochastic in nature, which is difficult to model using mathematical techniques, yet can be handled by machine learning techniques due to their ability to handle large datasets and identify patterns and make conclusions in new datasets.

Artificial neural networks (ANNs) are the most common machine learning technique used in the energy sector [28], being used to predict building energy demand, heating loads, HVAC demands as well as predict efficiency of renewable energy sources. Random forest regression, deep neural networks and support vector machines are also increasingly being used in the energy sector for determination of heating and cooling demands.

There is a increase in the convergance of both simulation with machine learning, due to the increased size of data sets and improvement in data evaluation such an approach can bring (Figure 2) [29].

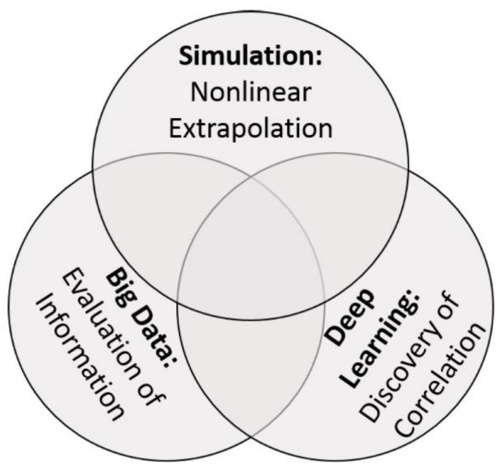



Figure 2- Collaboration of Big Data, Deep Learning and simulation [29]

The implementation of sensors for data collection in manufactuirng enevrionments can be intrusive, time consuming and expensive. Therefore utilising simulation can provide a method of data collection that is lower risk and of which can increase machine learning model training speed. Learning from simulation is increasingly becoming a pre-requisite for studies which require interactions with the real world [30], transfer learning, and is predicted to be the next driver of machine learning commercial success [31].

## 1.3 Thesis Structure

The structure of this thesis is as follows;

Chapter 1 provides context and an introduction to the subject matter within this thesis.

Chapter 2 provides a critical review of literature which identified research gaps. Such gaps in literature and knowledge provided a focus for the following research in this thesis. The aims and objectives to the research are stated.

Chapter 3 discusses the simulation methods adopted in this research along with underlying simulation theory and software justification. A case study is introduced, discussing data collection and HVAC control methodologies.

Chapter 4 introduces a number of predictive techniques utilised for the development of a proactive HVAC system. The use of simulation data for predictive model training is discussed along with statistical methods utilised in model validation. The highest performing predictive modelling method was subsequently utilised for prediction of peak energy demand and prediction of optimum HVAC set points.

Chapter 5 provides results obtained from investigations detailed in the preceding chapters of this thesis. A full comprehensive discussion of results is provided, discussing suitability of a proactive manufacturing-based HVAC system for manufacturing environments. The results and discussion identify research novelty along with strengths and limitations to the research.

Chapter 6 concludes the thesis, and discusses how the conducted research has achieved the objectives outlined in section 2.9, of which allows the overall research aim specified in section 2.8 to be achieved. The resulting knowledge contribution is highlighted, alongside areas for further work to build upon the conducted research.

Chapter 6 is followed by a complete set of references, listed in order of appearance.

The Appendix provides supplementary material for Chapters 3, 4 and 5.

# Chapter 2- Literature Review

## 2.1 Introduction

This chapter presents a review of current research undertaken in the field of energy and manufacturing facility analysis and identified a research gap which was the main focus of this research. The latest work performed in the field of manufacturing energy analysis was conducted, with a focus on holistic energy analysis of the manufacturing processes alongside the built environment and HVAC operation. Commonly used techniques such as simulation and machine learning are discussed, with the concept of Industry 4.0 for intelligent data analysis in manufacturing introduced. A summary of the literature review is provided, along with the identified research gap.

## 2.2 Energy Analysis of Manufacturing Processes

Simulation has been highlighted as the most appropriate method to model dynamic material and energy flows within a manufacturing environment due to the complexity of process interactions and large number of variables involved [32]. More specifically, Discrete Event Simulation (DES) is noted as being the most favoured method for modelling the dynamic nature of manufacturing process lines, as well as commonly being used to evaluate process operation and management, queue times, process optimisation, bottleneck identification as well as task scheduling [33]–[36]. DES is suited to the dynamic and often stochastic and non-continuous process of machining operations such as milling and turning process, due to analysis at discrete points in time. It has been noted that statistical regression models can be used for the analysis of manufacturing facilities due to their flexibility, low cost and limited amount of data required, however cannot consider the multiple technologies used in manufacturing facilities nor cannot identify potential improvements [37].

Software for manufacturing processes analysis include WITNESS, Plant Simulation, DELMIA, Arena, MATLAB with SIMULINK and FlexSim, however such software packages are aimed at increasing productivity and material throughput, resource allocation and utilisation, as well as reducing maintenance time and identifying bottlenecks rather than for analysis of energy flows.

DES analysis in manufacturing is predominately focused on resource management and efficient scheduling, mainly seen at machine level. For example Keshari et al. [38] utilised DES to investigate scenarios of varying production rate and resource management options of a paper and pulp plant. DES was used to model material flow from the entering location to the product collection point, with quantity of pulp fibre transferred from station to station representing the projected mass flow and capacity estimates of each station. The overall aim of the study was to achieve the optimal production rate and energy efficiency. Likewise Mouzon and Yildirim et al. [39] and Mouzon et al. [40] discussed frameworks to minimise energy consumption by schedule optimisation in manufacturing. Gul et al. [41] used DES to analyse a dental implant manufacturing facility in order to improve throughput, machine and worker utilisation as well as queue time, and was able to identify production bottlenecks.

Machine states are a common discussion in energy analysis, seeing DES being used for analysing energy consumption of actuators [42], with machine state and mode analysis for energy efficiency performed by Fysikopoulos et al. [43]. ElMaraghy et al. [44] presented a method of energy benchmarking of manufacturing lines, relating equipment energy data with machine states to allow for in-depth analysis of each machine, determining average energy consumption for different machine states (Figure 3). The concept was used to meet challenges of collecting and comparing data from different manufacturing facilities with different operational variants. Authors concluded energy consumptions for productive and non-productive states are close, highlighting the importance of optimising process planning and scheduling as well as better equipment utilisation.

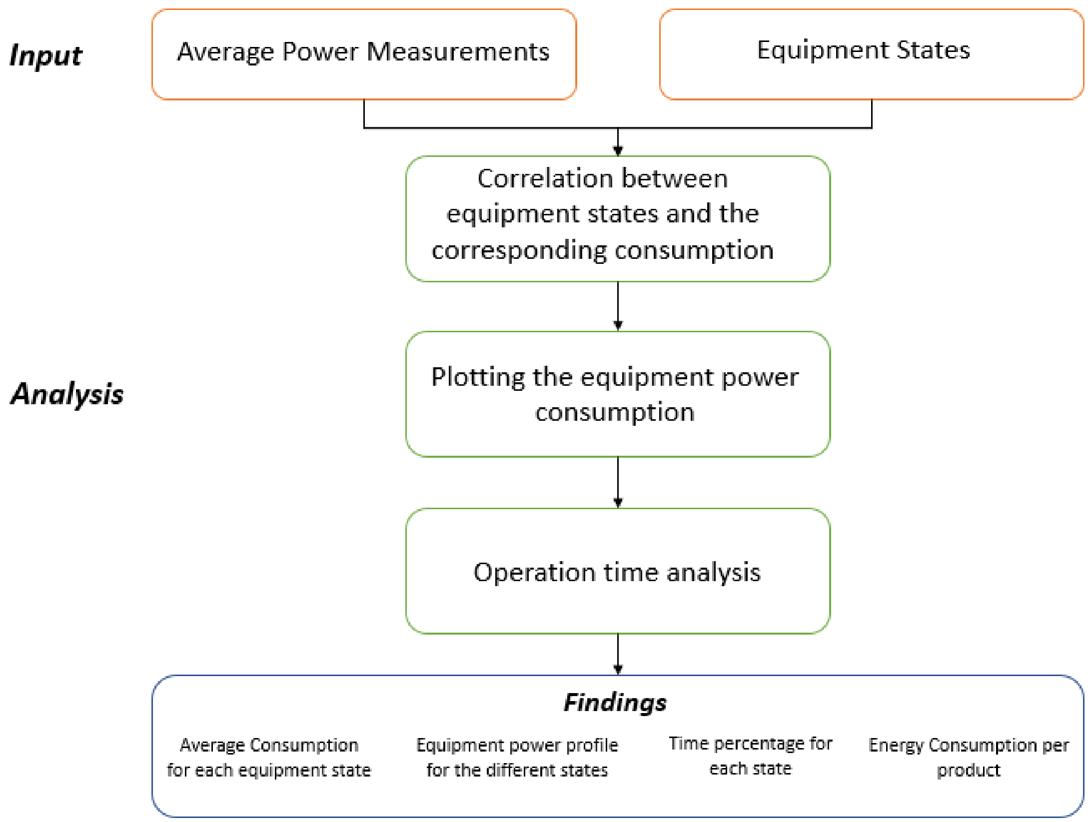



Figure 3- Collection/processing method for energy use data (figure reproduced from [44])

Furthermore, an exergy analysis, the potential of materials to do work, was carried out by Gutowski et al. [45] by simple mathematical calculation. Exergy was used to allow material and energy to be expressed in the same unit, Joules, as well as providing a measure of what is 'used up' in manufacturing processes. The study concluded the importance of process rate in estimating manufacturing energy requirements, and stated the need for redesigning manufacturing processes and increasing process rates.

Rodrigues et al. [46] proposed a method to analyse and optimise electrical energy consumption in manufacturing through the implementation of DES and optimisation software, investigating economic, social and environmental aspects for a more sustainable manufacturing process (Figure 4). Various scenarios were evaluated according to operational restrictions, with results evaluated according to objective functions in order to minimise energy consumption and satisfy sustainability indicators.

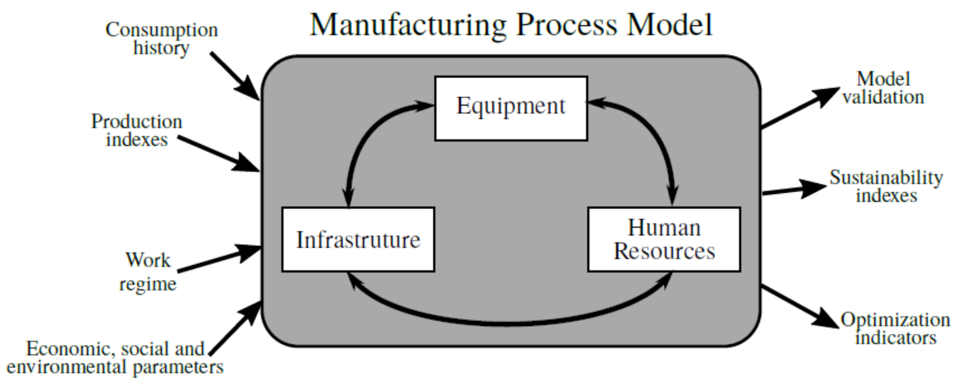
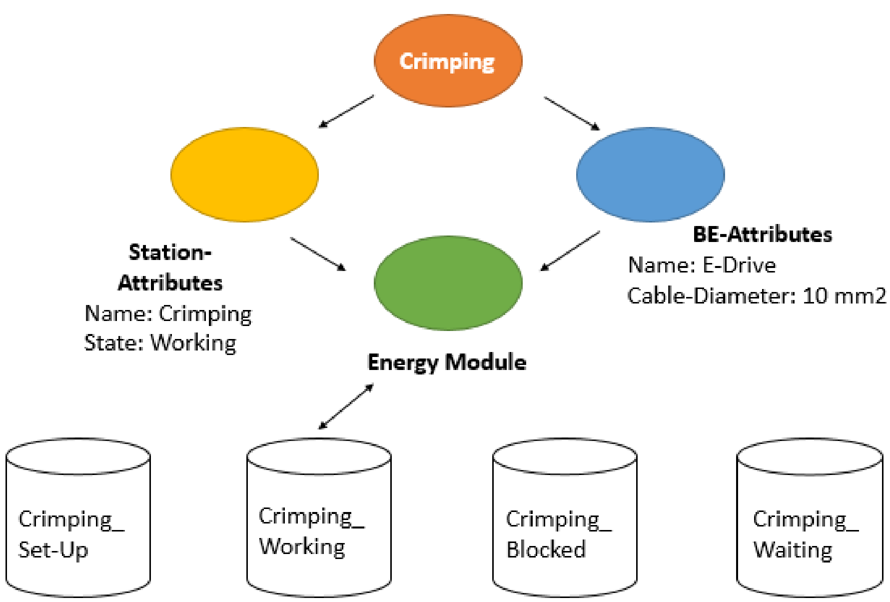



Figure 4- Manufacturing process conceptual model elements [46]

Although lighting was considered as an indirect consumption of energy, the focus of the tool was identification of energy losses in production, through consideration of production cycles, duration and process layouts.

Solding and Thollander [47] used an iron foundry as an example of a high energy consuming manufacturing environment, and developed a DES model with the aim of achieving an energy efficiency production plan without compromising output. Authors discuss the importance of reducing variable energy costs, based on actual energy consumption over a period of time, as well as grid costs, which comprises of charges for peak load. Thus stressing the importance of reducing energy consumption as a total but also peak energy demand from a financial perspective. However due to lack of detailed production data, hence inability to produce an accurate simulation model, authors focus on maximum load reduction rather than production planning. DES was concluded as a suitable tool for simulating energy use of energy intensive facilities, in addition to the traditional production planning techniques. The authors also highlighted the need and willingness of companies to adopt a greater level of understanding of company energy use, and without worker engagement an energy efficiency plan is worthless and impossible to implement.

Kohl et al. [48] introduced an energy module to be used alongside the commercial DES plant simulation software. After each machine state change, load profiles of machines were used to calculate energy consumption for each machine, with a resulting load curve for a full production line. The simulation was discrete in nature, however the resulting load profile was continuous, and the tool was able to provide more precise guidelines on the energy consumption of a facility. As the tool depended on the properties of the processed product as well as machine state, the tool required user input to define attributes which had to be considered for choosing the correct power profile (Figure 5). For example, the amount of material used in a process had to be selected as a factor that influenced the energy consumption. Such an energy module however provided a route to define product related parameters that influence the energy consumption of various processes.




| Time (s) | Crimping_ E-Drive_ 10mm2 (W) |
|---|---|
| 0.00 | 12013 |
| 0.10 | 12027 |
| 0.20 | 12042 |

Figure 5- User assignment of the load profile based on the attributes of the crimping workstation and the product (figure reproduced from [48])

Seow and Rahimifard [49] presented a framework of modelling the total energy required to manufacture a unit product, embodied product energy (EPE), using DES. The authors took a 'product view' perspective, in order to provide an estimate of the breakdown of energy use as well as total energy use. Plant and process level energy were considered, with energy consumed during processes such as casting, machining, painting, inspection at the process level, and energy for heating, lighting and ventilation at the plant level, in order to highlight any energy hotspots for further examination. The authors discuss the need for a greater transparency of energy use across manufacturing processes, and provided a model to support and identify operational improvements in a 'design for energy minimisation' approach (Figure 6).

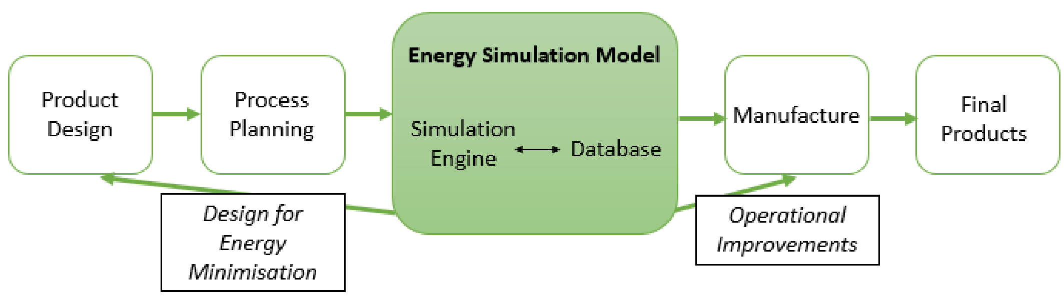



Figure 6- Design for energy minimisation approach (figure reproduced from [49])

However, the tool only analysed operational energy consumption, rather than energy consumed within a facility on a daily or weekly basis, nor stated the ability to analyse energy flows between the manufacturing processes, HVAC system or built environment.

Prabhu and Taisch [50] identified the importance of integrating machine level policy with production control policies to characterise energy dynamics and control the amount of wasted energy in manufacturing systems, through the use of DES. Energy control policy is described as the methodology in which to reduce the energy consumption when the machines are idle, thus the study focuses predominately on machine state change optimisation (Figure 7).

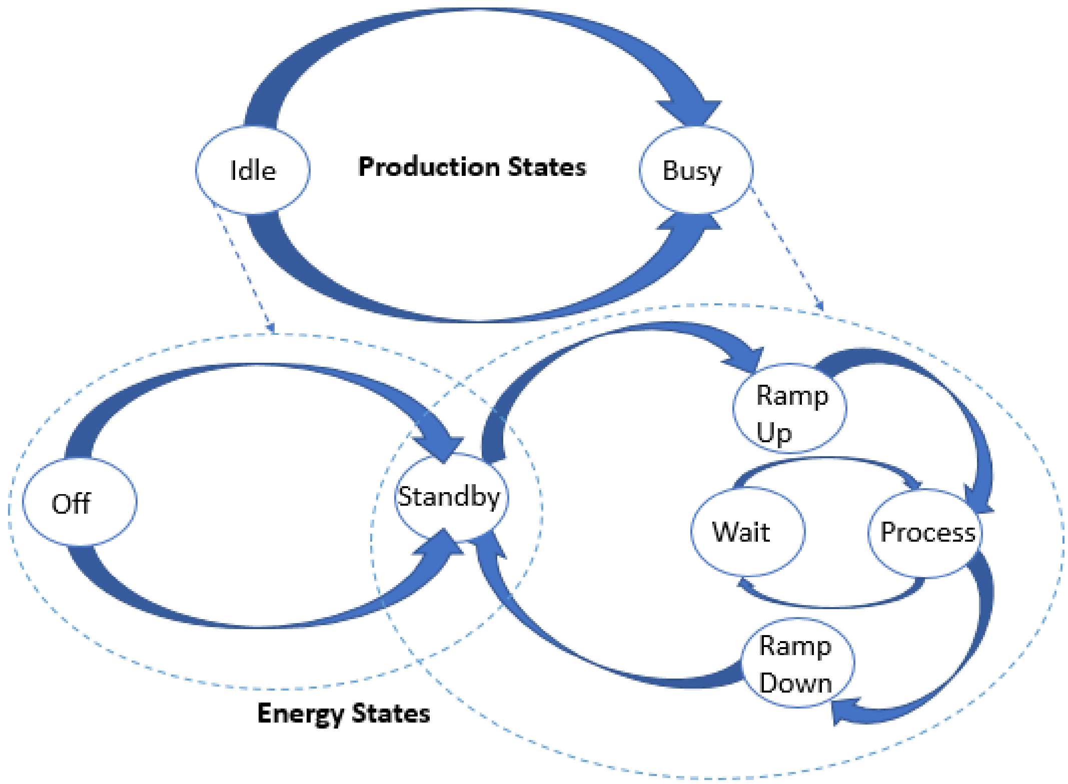



Figure 7- Mapping of discrete production states to energy states (figure reproduced from [50])

A software prototype HySPEED was developed, integrating continuously variable power consumption at the machine level with the discrete nature of the production control level.

Zou et al. [51] adopted a different approach, which used a continuous flow model to model a production line, employing sensor data from a manufacturing facility. The model was then used to identify and predict system performance and any energy saving opportunities, before implementing a real time feedback control scheme for further system improvements. Energy saving opportunity windows were investigated to avoid production loss, as well as stochastic and deterministic scenarios and system disruptions. The study reported significant reduction in energy consumption with minor influence to productivity.

Energy analysis or carbon emission analysis of manufacturing systems at tool level is seen extensively in literature, for example Tian et al. [52] who looked into the influence of wear conditions of cutting tools, establishing an optimisation model to determine cutting parameters and tools with the lowest carbon emissions. Likewise, Shi et al. [53] investigated the energy consumption associated with tool wear in milling processes, whereas Xie et al. [54] selected optimum turning parameters based on high surface quality and minimum energy consumption. Further studies analysed energy consumptions associated with machining processes such as multi-pass turning and multi-step milling [55], [56].

On machine level, Lv et al. [57] investigated the energy characteristics of a CNC machine, looking into various components of the machine such as the spindle and feed axis, as well as turning and milling processes. Whereas Zhong et al. [58] reviewed energy consumption models of machine spindle acceleration and rotation, machine tools and material removal, applying evaluation criteria to rank models for calculation of energy consumption in metal cutting processes.

### 2.2.1 Energy Management

Modelling of a manufacturing system is a complex undertaking, with multiple subsystems, and therefore various classification methods have been described. One of which is the 4 level organisational domain presented by Reich-Weiser et al. [59], encompassing a product feature level, machine/ device, facility/line/cell and finally a supply chain level. Furthermore, the authors discuss the orthogonal manufacturing perspective, describing the product design phase, process design phase, process adjustment phase and post-processing phase. Duflou, [60], however suggested a 5 level structure, of which comprised of a device/unit process level, line/cell/multi-machine system level, facility level, multi-factory system level, and the enterprise/global supply chain level.

From a managerial level, Schulze [61] and May [62] review strategies for energy management, discussing aspects such as strategy and planning, implementation and operational perspectives, organisation and culture. Similary, Cai et al. [63] proposed a concept of the lean energy-saving and emission reduction (LESER) strategy, used to determine value from the customer, environment, society and technology, as well as identify the value of energy consumption and waste emissions (Figure 8).

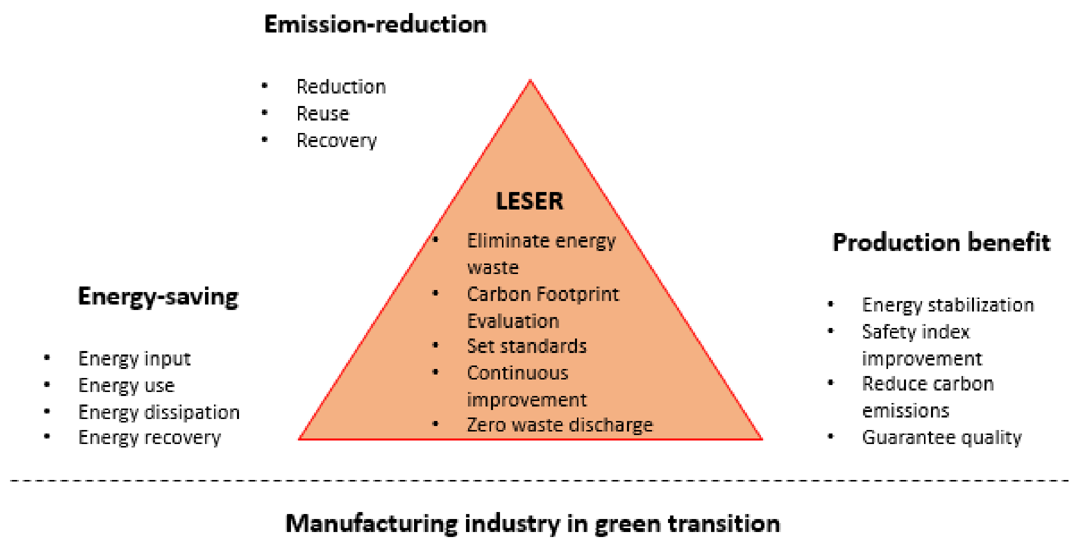



Figure 8- Strategy of the LESER tool in the manufacturing industry (figure reproduced from [63])

The tool considered energy input, use, dissipation and recovery from an economic, social and environmental perspective, with the goal of zone cost waste, zero emissions and zero pollution. The authors stated that workers are only responsible for 15% of energy related problems; the remainder attributed to system processes and thus was the focus of the tool strategy. The 5W-1H question method, (What, Where, When, Why, Who, How), was used to determine to root cause of waste and emissions.

Although providing strategies for energy management, the studies by Cai, Schulze, May, Duflou and Reich-Waiser focus on a wider perspective of energy use in manufacturing, rather than detailed quantitative analysis of energy consumption at machine, process or facility level.

Gahm et al. [64] developed a framework to guide research on energy efficient scheduling (EES) considering the transportation and conversion of primary energy sources, as well as applied energy sources (AES), such as electric current or natural gas, used for the production process (Figure 9).

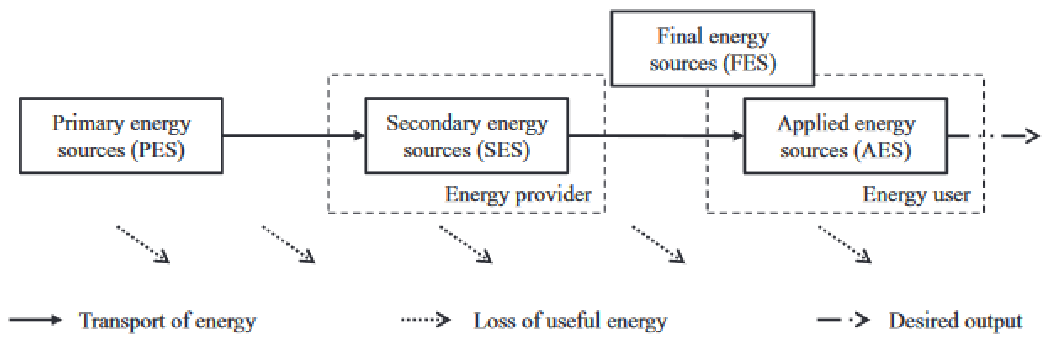



Figure 9- Energy conversion chain [64]

Energy unrelated to production such as climate control and lighting, which was stated as not being influenced by scheduling, is neglected. Scheduling was defined as the allocation of jobs to machines, and the associated sequencing and time on the machine. The authors discussed the role of production system energy and conversion energy in primary energy resource demand.

Feng and Mears [37] highlighted the challenge of modelling a manufacturing facility comprising of thousands of interacting production processes, and therefore presented a systematic modelling hierarchy of an automotive assembly plant with levels of models serving as different layers of organisational managers and technicians. The approach was able to efficiently identify energy critical components in the plant and highlight potential for improvement. The authors also discussed the use of systematic models in different levels on the holistic perspective of energy use, and concluded the inability for interaction between levels, therefore lacking in accuracy.

Many manufacturing facilities store off peak energy in thermal energy storage tanks or batteries. Machalek and Powell [65] discussed an approach using an energy peak-levelling algorithm which required minimal forecasting in order to tap into energy stores in order to put them on the smart grid. The algorithm took advantage of a thermal energy storage resource in a bakery which is subject to oscillations in the power demand, thus making them well suited to leveraging thermal energy storage. The storage tank at the facility along with the peak levelling algorithm was used to determine the power demand profile (Figure 10).

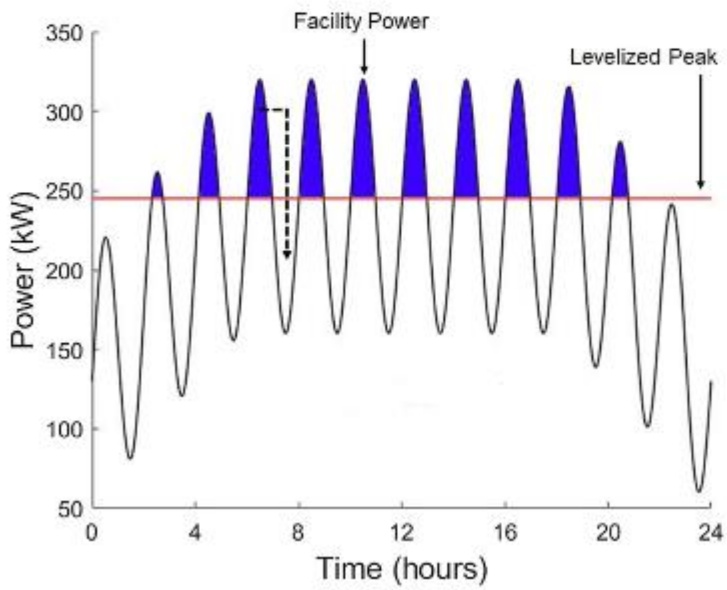



Figure 10- Peak levelling example of a facility power profile [65]

Authors state the advantage of not requiring a historical data set in order to level power oscillation and thus reduce power required. The method was able to reduce the energy by 2% over a monthly period.

### 2.2.2 Life Cycle Assessment

Life Cycle Assessment (LCA) is an environmental assessment method used by manufacturing companies to quantify environmental impacts of a product throughout its entire lifecycle. However such a method of analysis requires extensive data collection, thus a Life Cycle Inventory (LCI) database was developed providing average environmental impact data of various processes and materials; which many models are based-upon. However the accuracy associated with LCI data is debatable [66], with the energy requirements for manufacturing processes not being as consistent as LCI assumes [45].

Sproedt [66] integrated LCA with DES, looking at process inputs, process operation, cycle and set up times, scrap rates, waste materials and machine emissions. Lajevardi et al. [67] used LCA to analysis the energy consumption associated with different methods of manufacturing a heat exchanger for use in data centre thermal management.

Sector specific reviews on energy consumption and trends have been performed, an example seen from Ladha-Sabur et al. [68] who looked into the energy associated with food and drink manufacture. The review quantified energy consumption at various stages of preparation, production, transportation and storage of meat, dairy, fruits, vegetables and other household goods, including thermal processes such as freeze drying, and also the use of water consumption. The review was concluded by stating that strategies to optimise the food system, increase resource allocation efficiency and adopt tools such as LCA is required to achieve a better insight into energy end use.

The SIMTER tool, [69], was developed to cover the manufacturing planning phase, and cover four main areas, DES, ergonomics, levels of automation and environmental impacts along with conventional production simulation parameters in order to optimise the design of manufacturing systems (Figure 11).

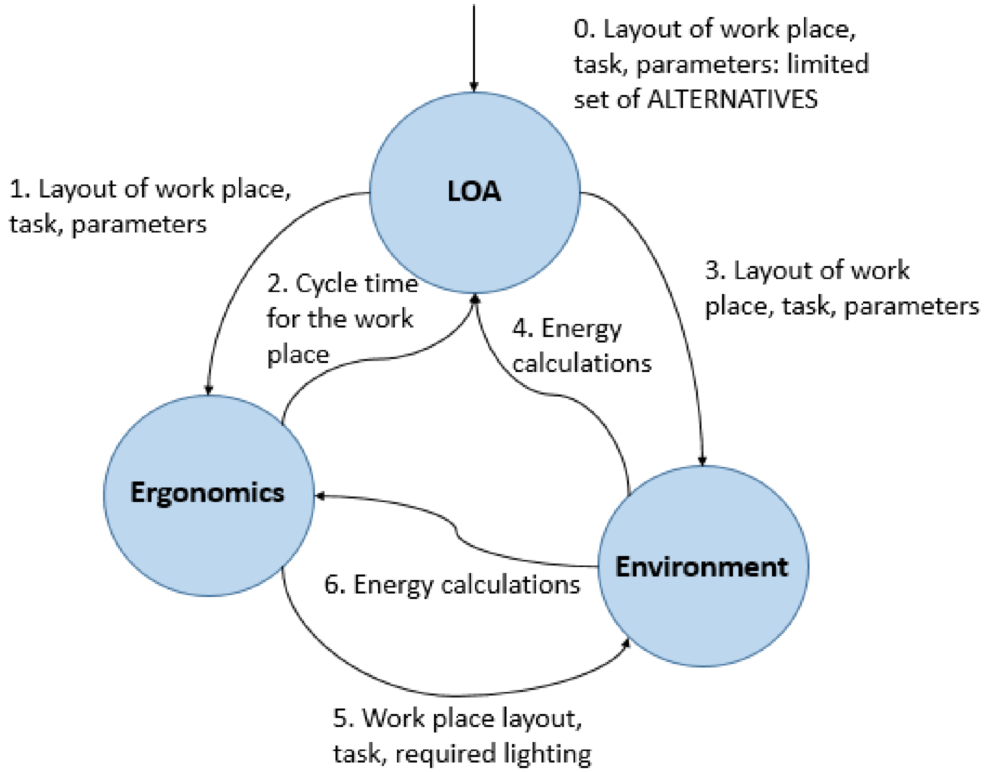



Figure 11- SIMTER tool, information flow and shared data within the tool (figure reproduced from [69])

Heilala et al. [70] utilised the SIMTER tool in a hybrid approach combining DES with analytical calculations. The tool was able to calculate energy efficiency, $CO_2$ emissions and environmental impacts of a manufacturing facility. Similarly, Johansson et al. [71] utilised the SIMTER framework to develop software showing how DES can be coupled with LCA to determine requirements for a sustainable manufacturing facility in the design stages. The tool was able to identify environmental bottlenecks such as energy consumption and carbon footprint in relation to the source of energy utilised. The study discussed $CO_2$ reduction goals, however rather than improving the energy efficiency of current processes, it was stated that the goals cannot be achieved with the current energy supply and thus renewable energy would be required for the environmental goals to be met.

## 2.3 Industry 4.0 and energy analysis

The concept of the fourth industrial revolution, Industry 4.0, brings an increase in digitalisation, automation and interconnected systems, with sensor systems allowing data to be captured at every stage a products lifecycle. Machines, production lines, raw material suppliers, management, distribution, customers and energy suppliers are linked through the use of IT, with data being harnessed for the use of simulation, machine learning and digital twinning, which has the potential to improve knowledge surrounding interoperability, productivity and energy efficiency (Figure 12).

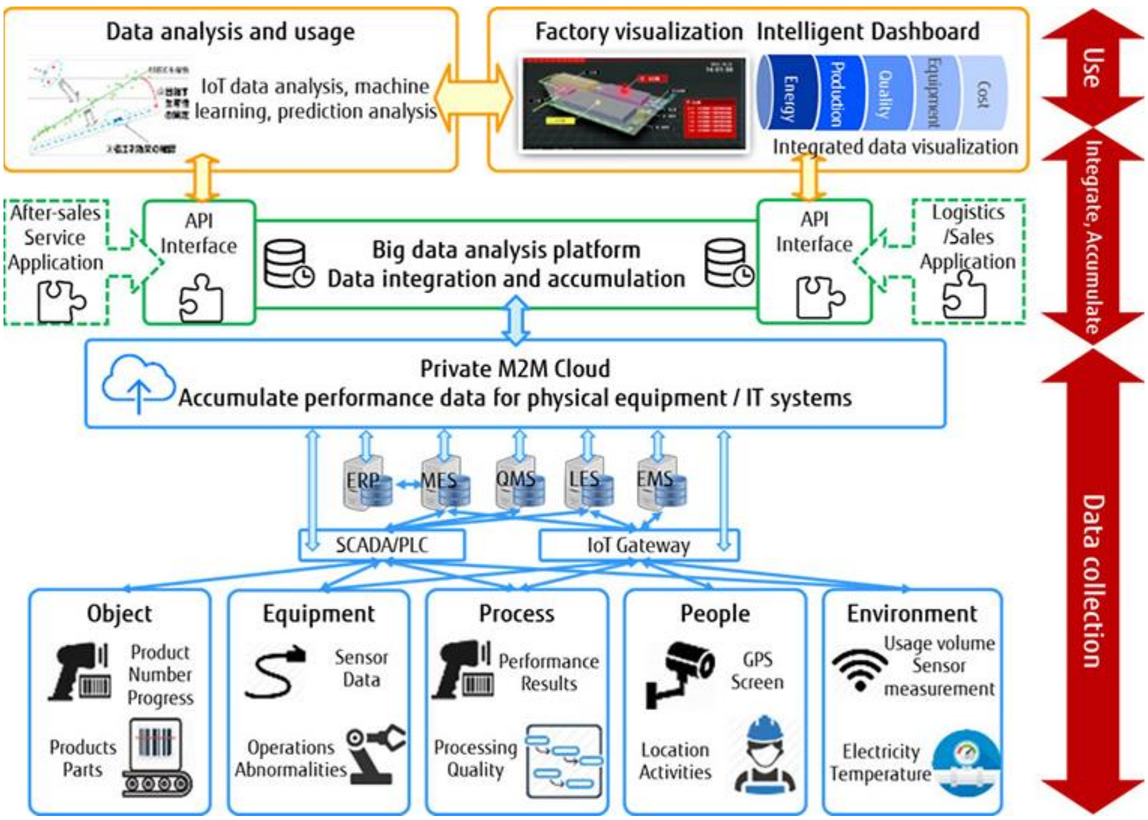



Figure 12- An architecture for smart manufacturing [72]

However, the concept of Industry 4.0 requires significant data storage capabilities and computing power, as well as initial costs associated with transforming a facility into a digital space through sensor implementation, employee training and cybersecurity considerations. This can be perceived to be a hindrance to SMEs due to limited knowledge, finance and resources.

Although DES is a common tool within manufacturing analysis, in Industry 4.0 DES is adopted as a tool for digital twin creation, and its use in industry 4.0 is predominately throughput and maintenance focused rather than for the use of energy analysis.

Cyber-physical systems (CPS) can be defined as the transformative technology between physical assets and computation, for managing interconnected systems [73] (Figure 13).

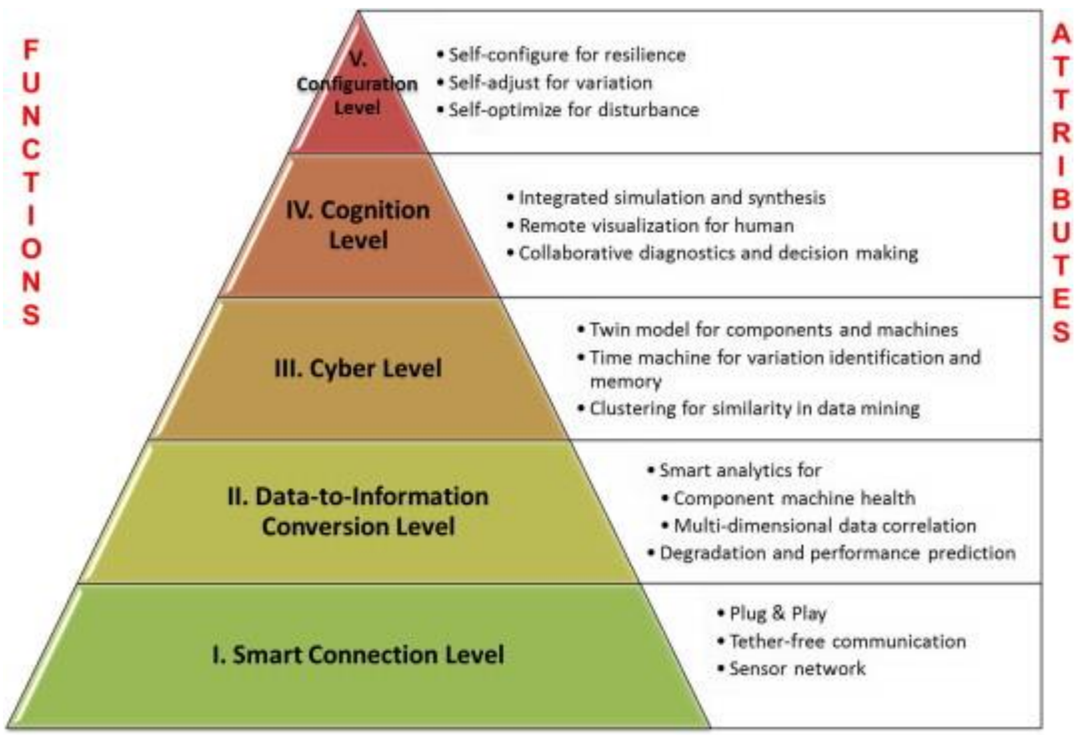



Figure 13- Architecture for implementation of cyber-physical systems [74]

CPS can be developed to manage big data and Internet of Things (IoT), leveraging the interconnectivity of machines and the production process, logistics and services, to develop an idealised fully connected Industry 4.0 concept. Big data refers to data sets which are too large to be managed using traditional approaches, and thus require specialist data collection, processing, analytical and storage tools. Recent studies have utilised CPS for resource planning and allocation in manufacturing [75]–[77], however Macana et al. [78] and Behl et al. [79] introduced energy cyber-physical systems (ECPS), and discussed their use in smart grids and university buildings, stating their potential for energy conservation and emission reduction.

However as the use of ECPS in manufacturing is limited, Ma et al. [80] addressed this gap by presenting an ECPS enabled management model to minimise emissions and waste whilst maximising output, integrating physical, energy and cyber worlds. The system comprised of 3 layers, a physical energy layer which included IoT devices such as sensors, the cyber-energy layer, which involved processing of collected data, and a data knowledge driven layer, which included the ECPS enabled management system, setting targets for energy conservation and emission reduction according to collected and mined data in the previous 2 layers (Figure 14).

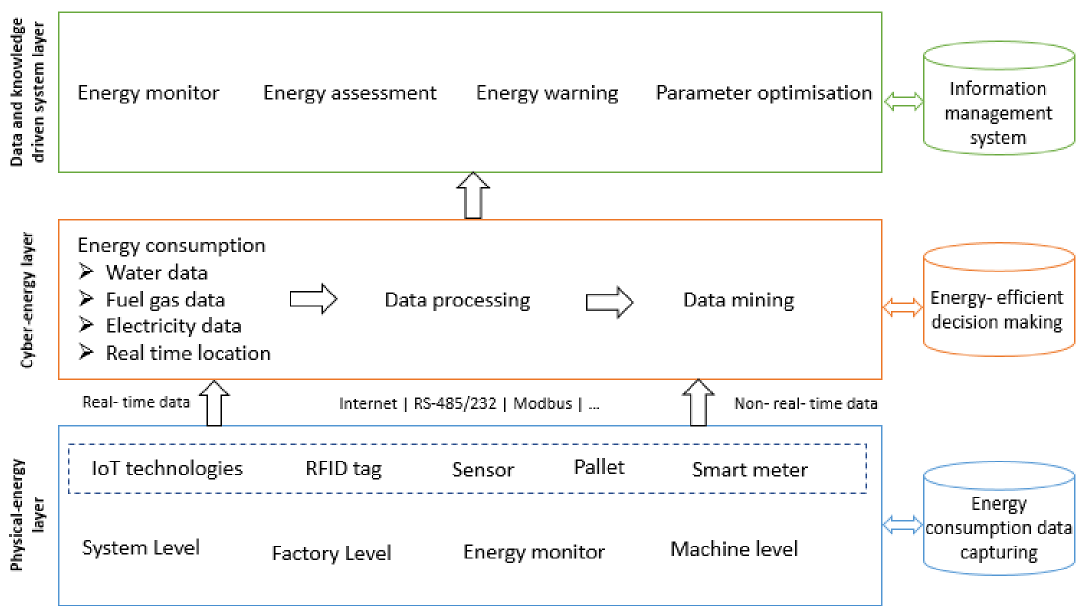



Figure 14- Architecture of ECPS enabled management (reproduced from [80])

A closed loop flow model was developed linking energy, material and information flows, analysing logistics, inventory, materials, production plans and performance, as well as energy related KPIs, energy management, recycling and energy reuse. The authors discussed the ability of the proposed structure to reduce energy consumption and emissions during the manufacturing process, however noted that the model was proposed without verification, therefore further work is required to develop the model further.

Saez et al. [81] proposed a real time performance assessment tool of manufacturing systems using hybrid simulation, utilising IoT to monitor the shop floor and synch real and virtual environments. DES was used to estimate performance at a system level, with continuous dynamics at a machine level, using a virtual environment running in sync with plant floor equipment. Real time monitoring allowed for direct comparisons between the virtual and real environment for abnormality detection. However the study did not analyse and discuss energy consumption, but was highlighted as an area for further work.

Edgar and Pistikopoulos [13] state that the integration of manufacturing intelligence in real time across a production operation does not exist, with decisions made with little knowledge on the relationship between product output and energy use. To bridge this gap, authors introduced the concept of a smart manufacturing system, which integrated simulation, modularisation, real time data, cloud technology, dashboards and performance metrics along with existing process control and automation systems. The aim was to improve system knowledge and product quality, reduce costs, improve energy productivity, workforce performance and safety. The authors discussed optimisation of steam methane reforming, a heat treatment furnace and a fuel cell system, using high fidelity models leveraging data from sensor systems in order to describe the systems and improve predictability of the model.

Similarly, Zhang et al. [82] proposed a big data driven framework along with big data mining to analyse and reduce the energy consumption and emissions of a pulp workshop, as well as optimising production processes and improving material and energy efficiency. The authors aimed to overcome the challenge of collection and analytics of multi-source and heterogeneous data from harsh environments such as high pressure, acid or high pollutant conditions. Furthermore, the authors presented a method of data mining to determine patterns and conclusions from collected data, as well as managerial perspectives from government, research and production departments (Figure 15).

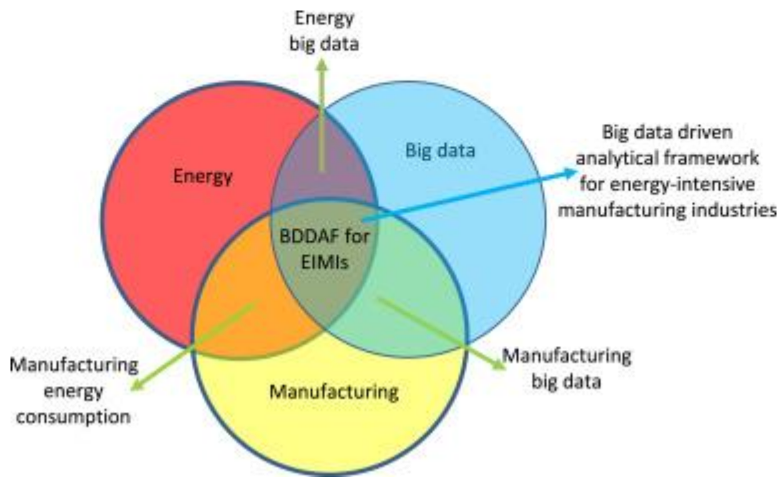



Figure 15- Interdisciplinary research areas of energy, big data, and manufacturing [82]

However the sensor technology was only proposed in the framework, implementation detail was lacking, and further work is required to determine a mathematical model for data mining to identify knowledge and rules from energy big data.

## 2.4 Coupling manufacturing with building simulation

Although DES is the preferred methodology at process level manufacturing energy analysis, such a process cannot account for energy flows beyond that of machining states, and therefore cannot model total facility energy consumption alongside manufacturing energy consumption. Although production based manufacturing is a discrete manufacturing process, the energy utility is continuous.

A study looking into simulation studies of which consider material flows along energy flows stated that of the 75 publications reviewed on simultaneous simulation of material and energy flows, 71% used DES, tools which combined DES with continuous approaches were used for 16% of studies. 7% of the reviewed studies included no statement on used tools [83]. A procedure model for combining material and energy flows was presented, with methods presented for decision making for the operation of 8 subsystems supplying the assembly and finish area of a car body shop.

Furthermore, manufacturing and industrial processes account for approximately 34% of Europe's overall heat demand [84], with heat loss from manufacturing equipment through electricity conversion further contributing to the waste heat within the sector. Although efforts have been made to reduce energy consumption and $CO_2$ through a products lifecycle, very few studies have looked into waste heat reduction or waste heat recovery. Medium grade waste heat (230-650°C) can be used for combustion or steam generation, however lower grade waste heat, typically found in large quantities from exhaust streams and compressors, can be used for space and domestic water heating [84].

The first found study investigating waste heat recovery was performed by Jeong et al. in 1998 [85]. The authors presented a numerical simulation to predict performance of a heat pump for low-grade waste heat recovery in a chemical plant. Similarly, Züst et al. [86] saw the potential of heat in industry, and predicted the potential of 32-80% for waste heat recovery within the manufacturing sector. The authors used simulation to estimate the heat released from machine tool subsystems in order to predict boundary conditions for thermal models in order to reach this potential. The approach required both datasheet values as well as experimentally obtained variables and it was stated that a methodology to predict such values was required to overcome this limitation.

Kurle et al. [84] used both simulation and mathematical optimisation to assess the waste heat potential of different production processes, and addressed the need to encompass different levels of manufacturing. A waste heat potential screening tool based on machine data was utilised to identify the more relevant waste heat processes prior to waste heat machine simulation. Waste heat load profiles were determined, with the final stage in the process being determination of process heating and cooling, and optimal waste heat exchanger design. The approach was described as a waste heat-planning tool that can identify waste heat potential on minimal information.

Similarly, Katunsky et al. [87] looked at thermal energy demand of an industrial building in Slovakia through the use of building simulation tools, ESP-r and BuildOpt-VIE. ESP-r was used for the dynamic simulation of machines and air movement, whereas BuildOpt-VIE was used to model the building in multiple zones, along with solar radiation. The study concluded that the machinery and occupants within the building are extremely influential factors contributing to the energy consumption of heating systems, and that methodologies adopted for measurement of temperature in residential or commercial building are not suitable for use in industrial buildings. Further work would include additional influential factors such as lighting, heat recovery and door opening systems, as well as multi-criterion analysis and energy auditing.

Weeber et al. [88] emphasized the importance of assessing interconnections between machine operation, process and factory infrastructure, and propose an integrated model in order to improve energy efficiency but also reap benefits of non-energy related factors such as thermal comfort (Figure 16). The authors translated machine load profiles into internal heat gain curves in order to quantify energy savings at factory level as a result of implementing energy saving measures.

However the study assumed 100% of measured machine power was transformed into thermal energy and the temperature of the surrounding environment was constant. Simulation was concluded to be a valuable tool and is required to determine impacts of optimisation measures for an increase in energy efficiency when considering the facility as a whole.

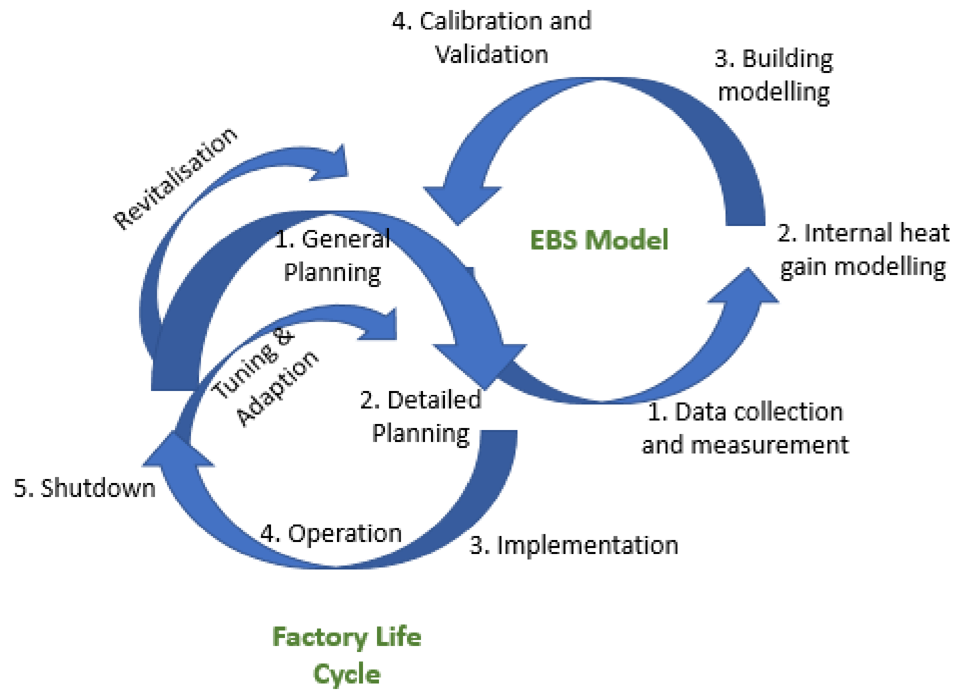



Figure 16- Energy building simulation methodology during planning and evaluation of energy efficiency measures (reproduced from [88])

Züst [86] looked at a single lathe in their study whereas Kurle [84] looked at an automotive process chain, but no studies were found to integrate technical building services (TBS) and building behaviour and use into the analysis and potential of waste heat for optimisation of HVAC systems.

Similarly on the topic of sustainability, Giampieri et al. [89] published an extensive review on the energy use and sustainability of automotive manufacturing facilities, with a focus on thermal management of low grade heat and the potential for heat recovery. The review covered vehicle production processes and process energy use, analysis of the paint shop and its components including different paint usage, as well as the future of the automotive sector discussing electric and autonomous vehicles with materials used and steps to low carbon production. The review concluded that the paint shop, being the highest energy consuming process, has a large potential for low temperature heat recovery with liquid desiccant technology; a potential method of providing significant economic and environmental benefits for the automotive industry.

Integrated DES modelling has also been considered by Wohlgemuth et al. [36] who presented an approach at linking DES with material flow analysis, along with Lu et al. [90] who presented an integrated DES and Building Information Modelling (BIM) framework. Both studies however focused on decision support, construction performances and resource planning rather than energy consumption.

Herrmann et al. [91] presented 3 paradigms which represent current research connecting manufacturing analysis with building energy simulation (Figure 17).

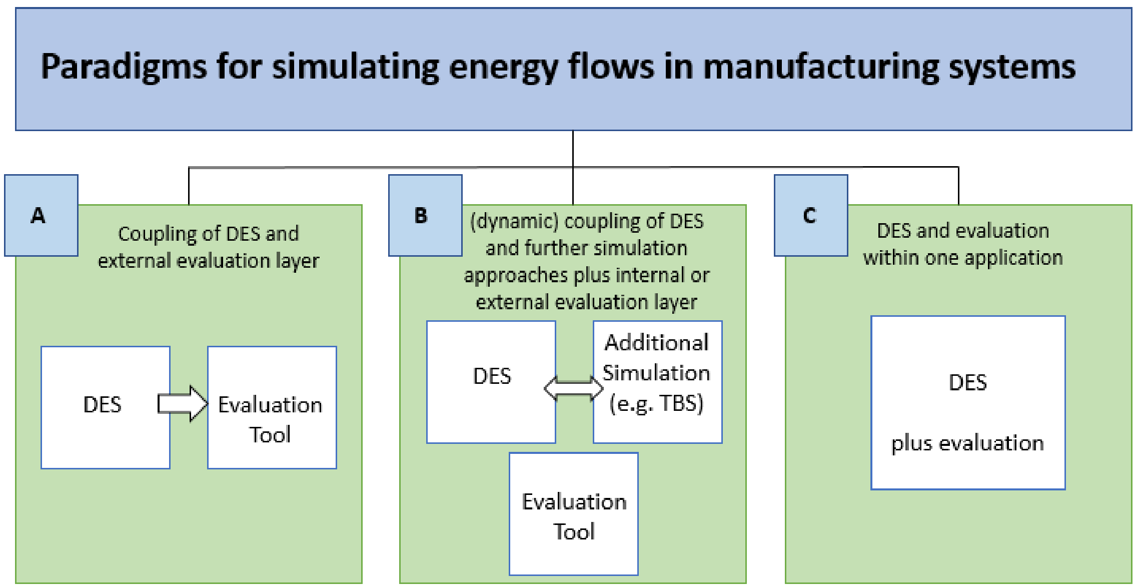



Figure 17- paradigms for simulating energy in manufacturing environments (figure reproduced from [91])

Paradigm A uses DES and evaluation tools, for simple low effort modelling. Such a method provides extensive coverage of energy and resource flows as well as distinctive evaluation, however simulation and evaluation sit independently from one another, and certain energy dynamics and interdependencies between systems are disregarded. Paradigm B introduced the additional simulation of TBS alongside evaluation, allowing the dynamics and interactions between subsystems to be considered, which considerably increases complexity of the model, and requires tools to be integrated and connected with suitable middleware. Paradigm C introduces a fully integrated system, encompassing DES, TBS and evaluation into one application. This usability of this system however is dependent upon simulation tools and limited by restrictions imposed by many softwares, and the task of integrating dynamic energy consumption, TBS and evaluation is not an easy one.

Hesselbach [92] and Herrmann [91] both discussed the importance of analysing the building shell alongside the manufacturing processes due to strong interdependencies between equipment and TBS. The former study adopted a hybrid multi-layer approach, coupling four discrete and continuous simulation tools for analysis of production machines and material flows, production management, TBS and climate (Figure 18), whilst the latter provided a single scalable and modular simulation environment with a hybrid approach.

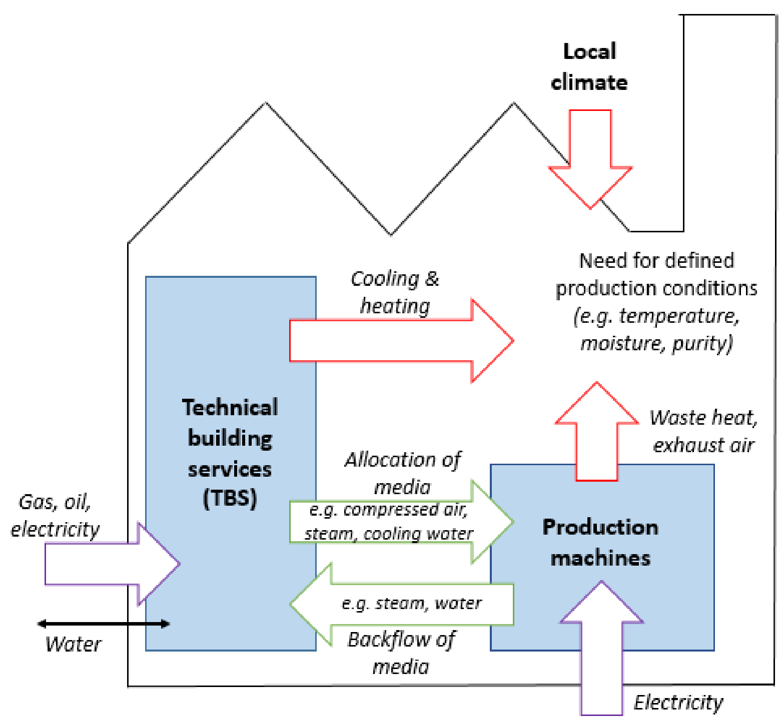



Figure 18- Interdependencies between production and TBS in defined production environments (figure reproduced from [92])

Case studies performed for both approaches confirmed the need for holistic simulation to identify and measure energy efficiency measures, however the studies did not analyse building energy consumption, nor model the HVAC systems, therefore the interaction between HVAC, building energy consumption and process demand is unknown. The tools were also deemed inflexible and cannot be applied to other production facilities.

Herrmann and Thiede [93] developed a process chain simulation to evaluate technical and organisational measures to increase energy efficiency from both an ecological and economic perspective. In order to cover all energy related aspects required, a five-step approach was developed (Figure 19).

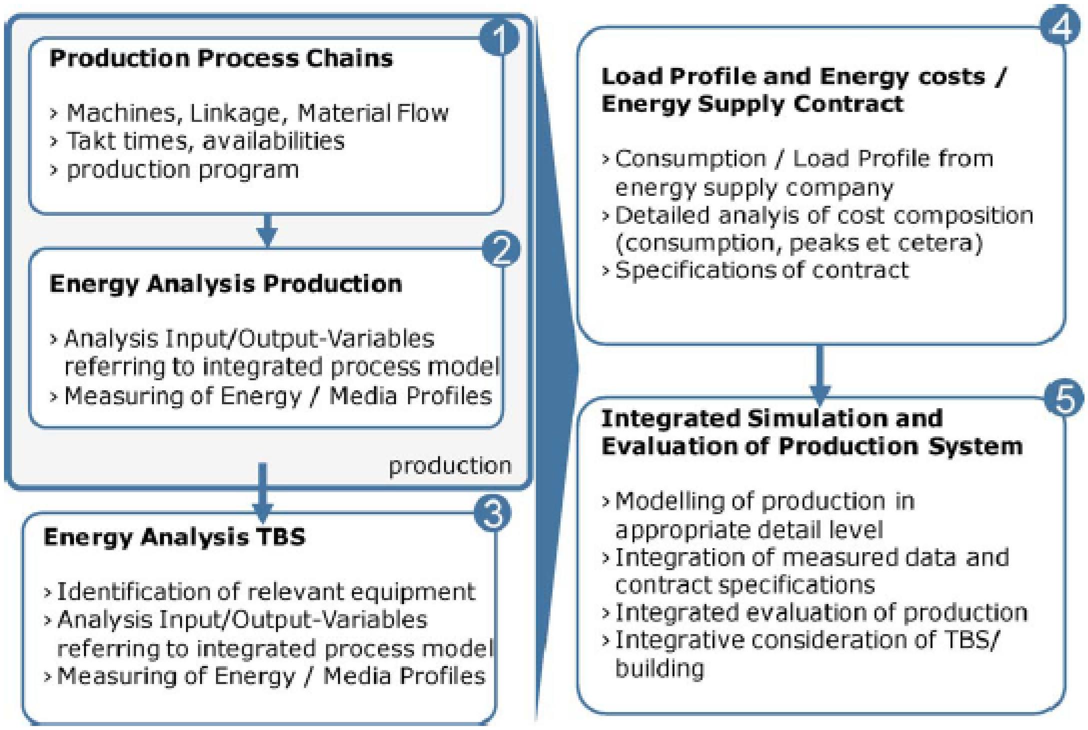



Figure 19- Systematic approach to increase energy efficiency in manufacturing companies further development

The authors concluded the necessity, potential and practical applicability of the developed method. The influence of production management measures on energy consumption were highlighted with measures on a single level, such as a production machine, described as not being sufficient to foster energy efficiency due to the influences of other levels.

Liu et al. [94] used EnergyPlus to evaluate and optimise the energy consumption of a welding facility, focusing on building design and manufacturing schedules. The overall aim was a reduction in energy consumption whilst maintaining production throughput. The authors highlight the interdependence between manufacturing processes and environmental conditions, and consider manufacturing equipment as internal loads within the building. Manufacturing energy consumption was calculated analytically, and subsequently added to the estimated building energy consumption for the facility as calculated by simulation. The concept achieved the optimisation goal, however authors state the need for the consideration of more control variables in order to simulate a more realistic environment.

Thiede et al. [95] presented a multi-level framework, involving coupling concepts and data exchange between manufacturing and factory simulation models, with assessment of energy demand, costs and environmental impacts (Figure 20).

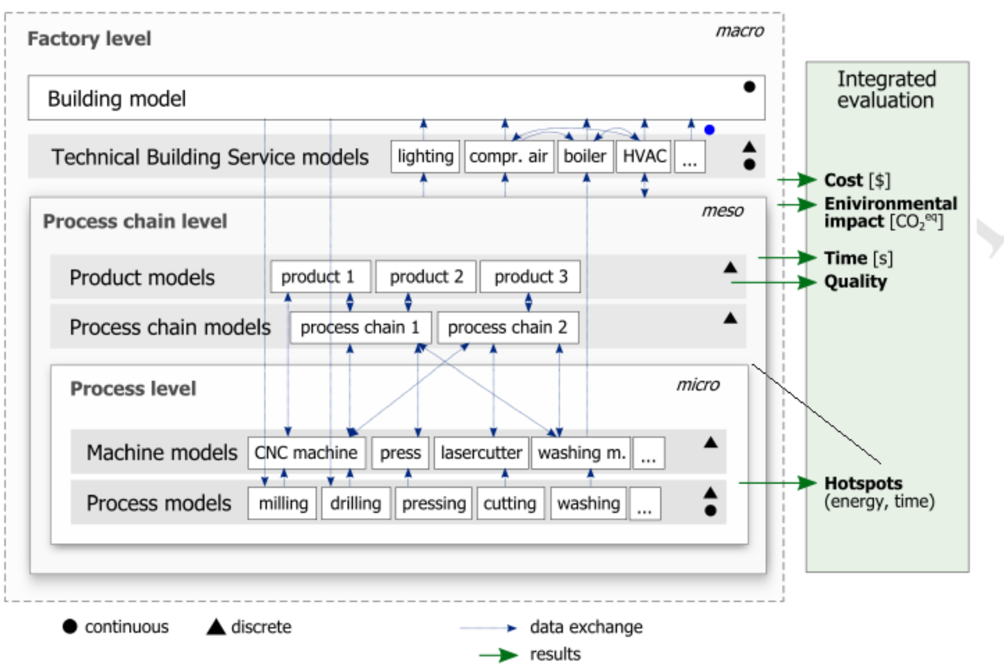



Figure 20- Framework for multi-level simulation models [95]

The authors applied the developed framework to the water-energy nexus of an automotive factory to highlight shift issues, and considered future planning with relation to energy and water targets (Figure 21).

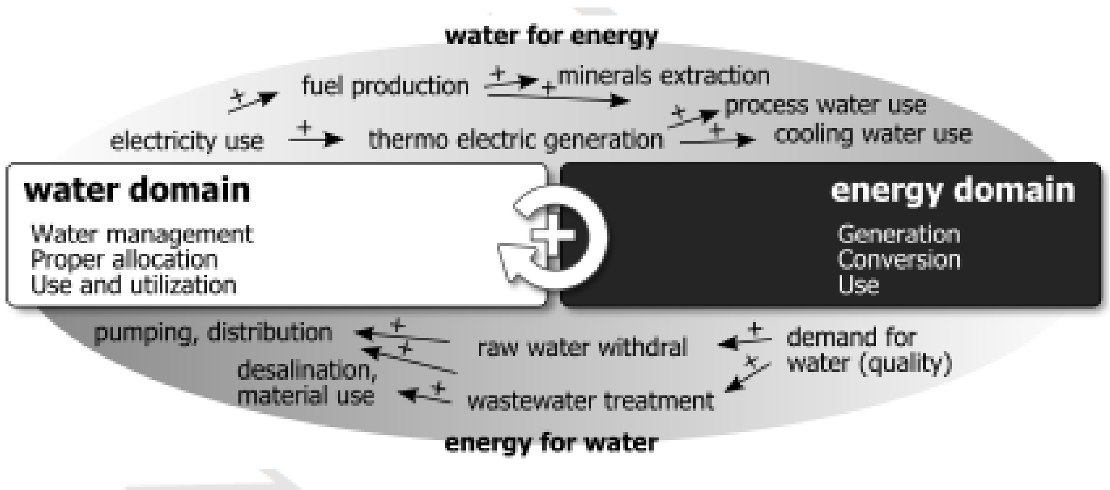



Figure 21- The relationship between water and energy [95]

Data handling and coupling concept recommendations were made, and the study highlighted the importance of a holistic simulation encompassing all relevant energy and material flows in order to fully reach energy saving potential.

Alvandi [96] used DES to tackle scheduling problems in multi-machine manufacturing environments. The tool comprised of a unit process module for machine representation, a process chain module, and a TBS module for supplying services such as steam, compressed air, air purification along with lighting and heating services. With the use of a case study, an optimisation tool was used to determine the best routing for each product type with a goal of minimising energy and lead-time whilst maximising throughput. However the proposed optimal solution resulted in a 51% increase in throughput, with an energy consumption increase of 5%, rather than a decrease in energy.

Michaloski et al. [97] investigated the integration of manufacturing execution systems (MES), which controls production activities, and energy management systems (EMS), which controls energy related activities. MES uses production planning to assign factory resources whereas EMS manages power distribution, HVAC, lighting and compressed air. Data exchange between these systems is commonly limited, which limits the ability to understand interactions between the production environment and energy flows, making sustainability improvements difficult. The study utilised DES to analyse requirements of the integrated EMS-MES system, and investigate sustainability opportunities. The authors were posed with the common challenge of data integration, with the need for a suitable data resolution, resulting in the simulation of energy being performed in parallel. Further work is required to validate the tool, along with tests on a case study environment.

Bleicher et al. [98] utilised three simulation models for a co-simulation approach at analysing energy consumption of a manufacturing facility- MATLAB was utilised for data models of machine tools and production schedules, Dymola for the energy system and EnergyPlus for building models (Figure 22).

The Authors stated that the use of three sub-models allowed for deeper scenario investigation to determine energy saving measures due to clearly defined interfaces, and ability to replace sub models without impacting other parts of the system. Parameters considered in the model included machine energy consumption, machine internal energy conversion, machine thermal behaviour, building energy systems along with sub systems such as pumps, chillers and heaters, as well as thermal aspects of the building such as occupancy heat gains, lighting and computers, and building geometry, structure and floor layout. Although the tool could provide energy demand predications in the facility planning stages, authors posed difficulties associated with time resolution of sub modules, with machining simulations utilising time in the order of milliseconds and energy simulations in the order of multiple minutes. Furthermore, the coupled simulation presupposes requirements to the sub models, impacting the accuracy of the model.

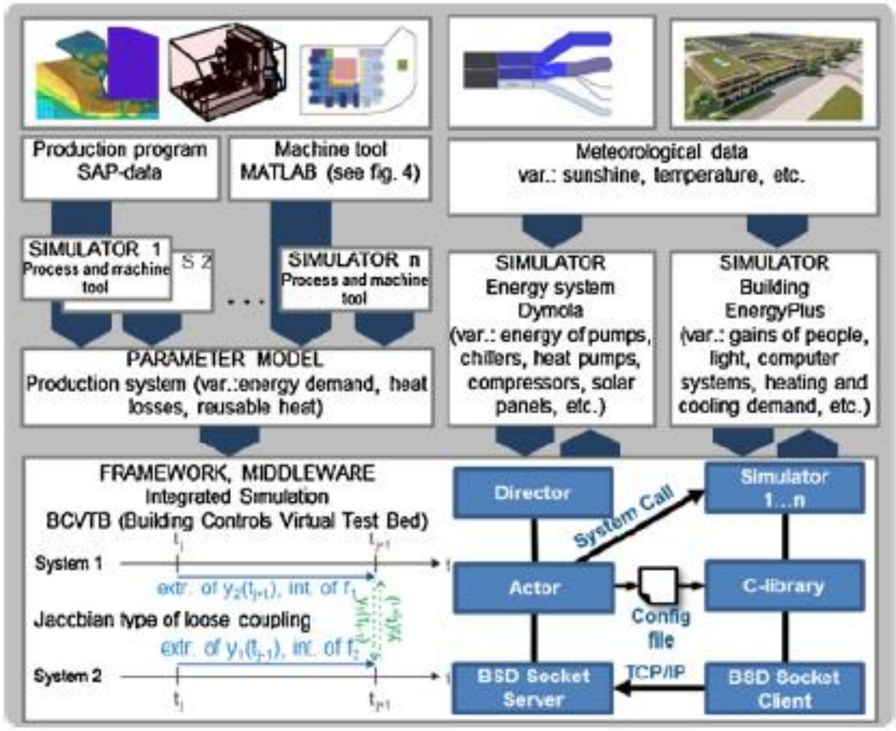



Figure 22- Methodological approach [98]

Aiming to solve the issue of data resolution in hybrid models as found by Bleicher and Michaloski. Liang and Yao [99] introduced a hybrid analytic and simulation approach, adopting a multi-resolution approach. Arena was utilised for the workshop level, with MATLAB utilised for the machining state level and cutting level, with VBA and excel used as communication between the two. Authors concluded feasibility of the proposed approach, however no case study application, data collection or methodology was discussed, nor the inclusion of TBS or thermal flows.

Schönemann et al. [100] presented a multi-level simulation framework connecting a DES process chain simulation with a physical process model in order to derive LCA relevant data (Figure 23).

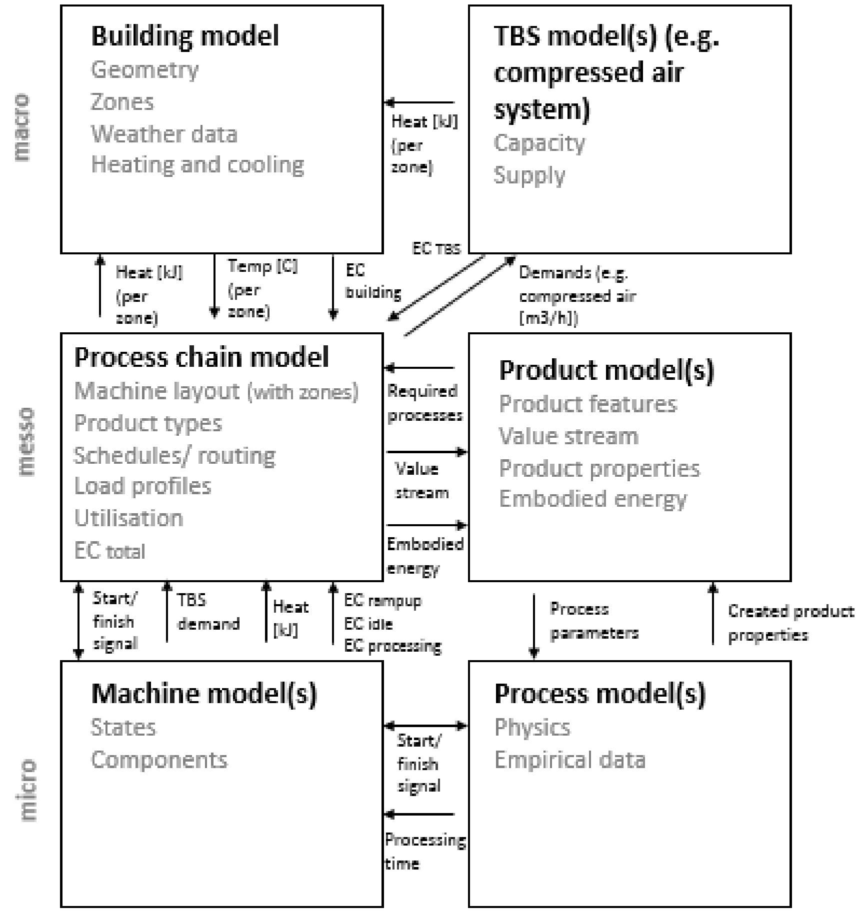



Figure 23- Multi-level framework for holistic analysis (figure reproduced from [100])

AnyLogic was utilised to model the process chain, with MATLAB used for modelling a single process. Coupled models were able to compare the environmental impacts of two product design alternatives in the automotive sector. The authors stated the tool provided a good foundation for consideration of product life cycle data from material flow in production to energy demand in the design phase, however further work is required to validate the model, perform parameter sensitivity analysis and reduce number of assumptions made in model development.

Ball et al. [101] presented a model coupling material, energy and waste of a manufacturing facility to show how these flows interact with the surrounding manufacturing environment, with the aim of developing a zero carbon manufacturing facility (Figure 24).

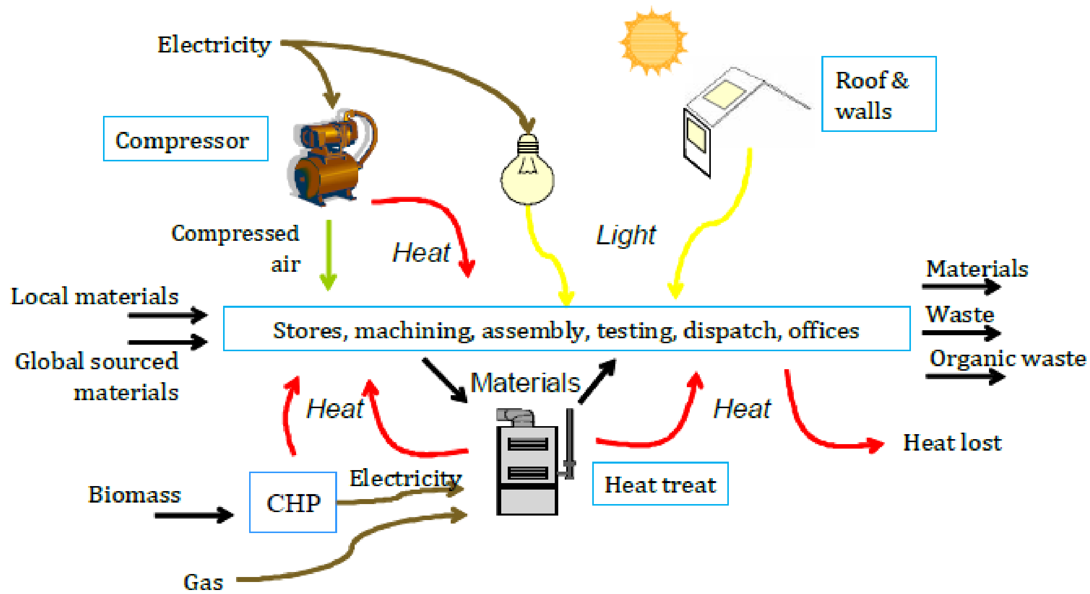



Figure 24- Light and heat flows in a manufacturing operation [101]

The production system, infrastructure (offices and facilities) and interface with the supply chain and community were encompassed within the zero carbon ideology. The authors discussed renewable energy, replacement of old machining with newer more efficient systems, reducing inventory, packaging types with supplier collaboration, recycling and conversion of waste to energy through the use of biomass. The authors however did not detail individual manufacturing processes, and the approach presented was qualitative, acting as a starting point for further investigation. The approach did not model magnitude, location or quality of flows within the facility, nor was the approach dynamic.

Wright et al. [34] introduced the THERM project, which provides the concept of software tools to model energy and utility flows in manufacturing, allowing them to be integrated into thermal modelling of buildings. The tool allowed for the representation of continuous material flow, energy and water as well as their interaction with TBS. Building geometry, thermal characteristics and use were also accounted for, along with the flow of electricity, water and steam.

Oates et al. [102] discussed energy flow paths in a factory environment, (Figure 25), and identified three 'types' of manufacturing processes to be analysed using the THERM tool; thermal 'air' processes (oven), thermal 'fluid' processes (vat) and electrical processes (motor).

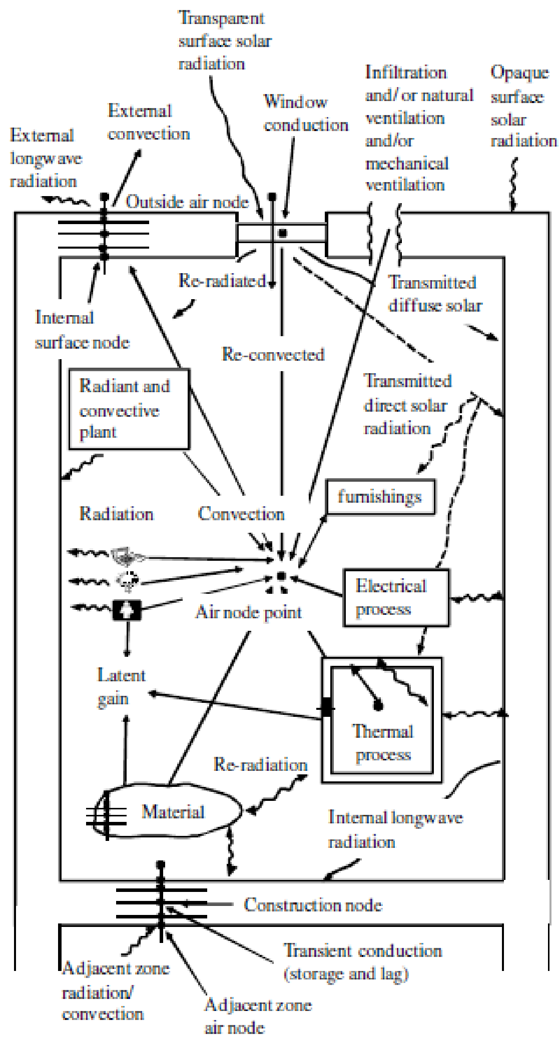



Figure 25- Schematic of the overall energy flow paths of a factory environment [102]

A library of 'tactics' was created to determine actions which can be taken to improve efficiency of production, resource use and reduce energy. Initially, prototype models were created to estimate energy savings from certain processes, with software developed by IES Ltd, which was to be integrated into their commercially available software tools. However the authors concluded that the actual development of such a tool would be a major undertaking, and discuss the difficulties arising from data requirements and collection, such as data management, format and availability.

The THERM project was extended further into the REEMAIN project, which included modelling of energy generation technologies as well as an Organic Rankine Cycle (ORC) in order to generate electricity from waste heat. Greenough et al. [103] discussed the development of the project, discussing the integration of a decision support tool in relation to renewable technologies. However the ORC tool is yet to be developed, and currently a fully integrated dynamic simulation is not yet possible. Furthermore, Despeisse et al. [104] worked on an aspect of the THERM project, presenting a tactics library linking sustainability with operational practice, which was then used in a factory model to combine building energy analysis with manufacturing resources. The focus of the tool was sustainability, providing a guide of modelling and optimising resources.

Building energy consumption analysis is commonly based upon degree-days, however such a methodology results in the building energy performance being a function of degree-days, whereas many other influencing factors have an impact on energy performance. Although such a methodology has been criticised in the past, with work carried out to determine new base temperatures [105], [106], and despite the harsh environmental conditions manufacturing facilities experience, little work has looked into the suitability of degree days as a methodology of building energy analysis for industrial facilities. Golden et al. [107] analysed two regression models, a three change point and cooling degree-day (CDD), for creating baseline energy models in industrial facilities and determining energy end usage. In the three-change point model, energy use remains constant up to the base temperature, at which point energy use increases linearly. In the CDD model, energy consumption is computed using degree-days based on the base temperature (Equation 1), where only the positive temperature differences are evaluated.

$$CDD_i(T_{b,c}) = \sum_{j=1}^{N_i} \left(T_{amb,ij} - T_{b,c}\right)^+$$

Equation 1- Cooling Degree Days ([107])

Where $T_{b,c}$ is the base temperature (K) and $T_{amb,\,ij}$ the average outdoor air temperature (K) for the jth day of the time interval i.

Authors also presented a variable base temperature CDD method, which utilised a weather independent variable, however the method also utilised an averaged CDD value calculated from Equation 1.

Conductive heat gain, $\dot{Q}_{cond,annual}$ (W), and infiltration heat gain, $\dot{Q}_{inf,annual}$ (W), was calculated based on CDD utilising Equation 2 and Equation 3 respectively.

$$\dot{Q}_{cond,annual} = \frac{CDD}{R}$$

Equation 2- Conductive heat gain through the building envelope ([107])

Where R ($W^{-1}$ $m^2$ $K$) is the thermal resistance through the building envelope.

$$\dot{Q}_{inf,annual} = \dot{m}c_p \, x \, CDD$$

Equation 3- Sensible Heat Gain from Infiltration and Ventilation ([107])

Where $\dot{m}$ is the mass flow rate ($kg\ s^{-1}$) and $c_p$ the specific heat capacity ($J\ kg^{-1}\ K^{-1}$).

In order to estimate motor power and HVAC load required from internal heat gains, the energy consumption was estimated through the use of a weather independent variable.

For the three-change point and CDD method, the $R^2$ (coefficient of determination) value indicated a poor relationship between ambient temperature and facility energy use, however the NMBE (normalised mean bias error) meets the ASHRAE (American Society of Heating, Refrigerating and Air Conditioning Engineers) requirements for goodness of fit. For the CDD method, CV-RMSE (coefficient of variation of root mean square error) did not meet requirements, but was satisfied for the three-change point method. Although the CDD method did analyse energy consumption to a reasonable degree, the use of weather independent variables and further calculations were required to determine effects of internal gains.

## 2.5 HVAC optimisation in Manufacturing

Wang and Ma [1] produced a review on supervisory and optimal control of HVAC systems, stating that operation and control of a HVAC system significantly impacts the energy or cost efficiency of buildings, and is not solely dependent on its design. Determining the optimal control of a system which provides thermal comfort and a healthy environment can improve energy and cost efficiency.

After process heat generation, the largest energy consumer in manufacturing facilities is the demands from HVAC systems and lighting [108]. In manufacturing facilities, HVAC systems are commonly installed as a centralised unit, with very little feedback and control from the supplied area, resulting in ineffective and less than optimum distribution of heat and air, as well as not being able to account for differences in different condition requirements across the facility. Thermostats or temperature sensors are often placed next to ventilation shafts or heaters, leading to dependence on a singular measurement for facility control, with regard to a singular area, resulting in under or overheating of surrounding areas. For accurate determination of facility temperature and required HVAC control, thermal energy flows and air flows within the facility need to be determined. Therefore, Posselt [108] used computational fluid dynamics and a wireless sensor network to estimate temperature and air flows at every position in a building in real time in order to improve control strategies of HVAC systems. A total of 38 sensor nodes were placed strategically to achieve maximum distribution and minimum overlap in the facility, with locations including working height, floor level, close to doors to capture temperature drops, above heat emitting machines and downstream of circulation fans. The prototype provided insight into thermal energy flows within the building, and was believed to hold potential for optimising HVAC dimensions, as well as determining negative effects of zone/window operation or alternative factory layout.

Research into peak load reduction in the industrial sector is not as well developed as in the commercial and residential sector, resulting in a low level of actual peak demand reduction compared to its potential (Figure 26).

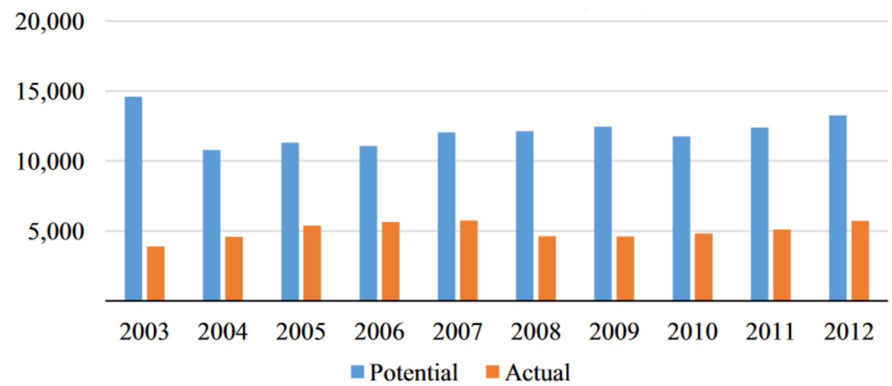



Figure 26- Demand side management- industrial sector peak load reduction. Comparison of potential and actual peak load reduction in the industrial sector (MW) [109]

Therefore, Dababneh [109] investigated electrical demand response, and developed an analytical model to reduce peak power demand using a HVAC working load model integrated with the manufacturing system. Heat transfer characteristics of five machines and four buffers were analysed to determine the effect of the equipment on a HVAC system, with manufacturing production then scheduled during off-peak periods to reduce HVAC power demand during peak periods. Focus was on peak-power demand reduction rather than overall energy consumption of the facility.

Similarly, looking at machine schedules and peak demands, Brundage et al. [110] adopted the idea of an energy opportunity window, which allowed machines to be turned off at certain times without any reduction in throughput, with the aim of a reduction in energy consumption. The authors synced the energy opportunity window with times of high energy demand of the HVAC system in order to optimise facility energy use. The thermal model was able to account for environmental changes such as air temperature, heating loads and solar radiation, however a continuous flow model was used for the manufacturing production line, so cycle times were assumed a constant with down times of machines not considered. Although the method achieved a reduction in cost, the study was focused on scheduling and financial savings rather than determination of energy consumption and analysis of interdependencies between the manufacturing systems and built environment.

Alongside the previous studies focusing on schedules, operational strategies and planning, Sun et al. [111] considered the HVAC system alongside the manufacturing systems in order to determine an optimal demand response strategy for the facility. Optimal production schedules and power curves from the manufacturing systems along with building characteristics drove an EnergyPlus simulation. Particle swarm optimisation was determined by the facility production capability, electricity pricing, power limitation and ambient air temperature in order to determine the demand response strategy. Although the authors considered the HVAC system alongside the manufacturing processes, significant simplifications and assumptions of the facility were adopted, such as constant HVAC performance, constant outdoor temperatures with no mention of convective or radiative heat transfer from machines, and therefore the facility was not representative of a real facility. The authors discussed further plans to relax simplifications and provide real time decision making.

## 2.6 Predictive techniques

Multiple authors have reviewed techniques for energy demand forecasting or electrical energy use prediction. All studies concluded the most popular technique was the use of methods using artificial intelligence (AI) such as neural networks or support vector machining, of which greatly outweighed the use of other techniques such as statistical regression [112], [113]. The accuracy of AI methods have also been seen to outperform statistical methods [112].

### 2.6.1 Regression for energy prediction

Statistical regression models are used to determine a relationship between input and output variables based on a set of historical data. In the area of energy use analysis, regression models have largely been used to determine the relationship between variables such as weather, price or customer income with energy use in the residential and commercial sector.

Egelioglu [114] used multiple regression analysis to determine that customer numbers, price of electricity and number of tourists correlate with annual electricity consumption of a region in Cyprus, and therefore such variables can be used to forecast future annual electricity consumption. Likewise, Bessec [115] used statistical regression techniques to investigate the relationship between electricity demand and temperature in Europe.

In the industrial sector, Al-Ghandoor [116] used multivariate regression to determine that the most important variables to impact electrical power demand was the industrial production output and capacity utilisation.

A few studies have adopted regression-based methods for the prediction of energy demand and load forecasting in the commercial and residential sector.

Ma [117] used multiple linear regression techniques to predict the monthly energy consumption for large commercial buildings, whereas Cho [118] used regression techniques to predict annual heating energy consumption of a commercial building, comparing different measurement periods. The study concluded the importance of providing enough data to produce an accurate model for energy predictions.

However due to their simplicity, statistical regression models lack flexibility and require a large amount of data to draw any significant conclusions and relationships between data. Most regression techniques are unable to deal with the nonlinear behaviour of energy use and efficiency in buildings [113].

### 2.6.2 Machine learning for energy predications

The most common machine learning technique within the energy sector is the use of Artificial Neural Networks (ANNs), with their use being adopted in residential and commercial buildings, looking at heat loss, electric efficiency, occupant energy use or building energy use, each of which can be classed as a micro model. A macro model, is one which encompasses multi fuel, multi sector and region analysis, such as district or country wide energy predictions [119]. Such models are also increasingly being used to predict solar radiation or wind speeds in order to maximise renewable energy output through efficient planning and resource utilisation [120], [121].

One of the first found studies using ANNs for energy demand forecasting was performed by Javeed and Al-Garni in 1995 [122], who utilised ANNs to forecast electrical energy consumption in the Eastern Province of Saudi Arabia based on weather, global solar radiation and population (Figure 27).

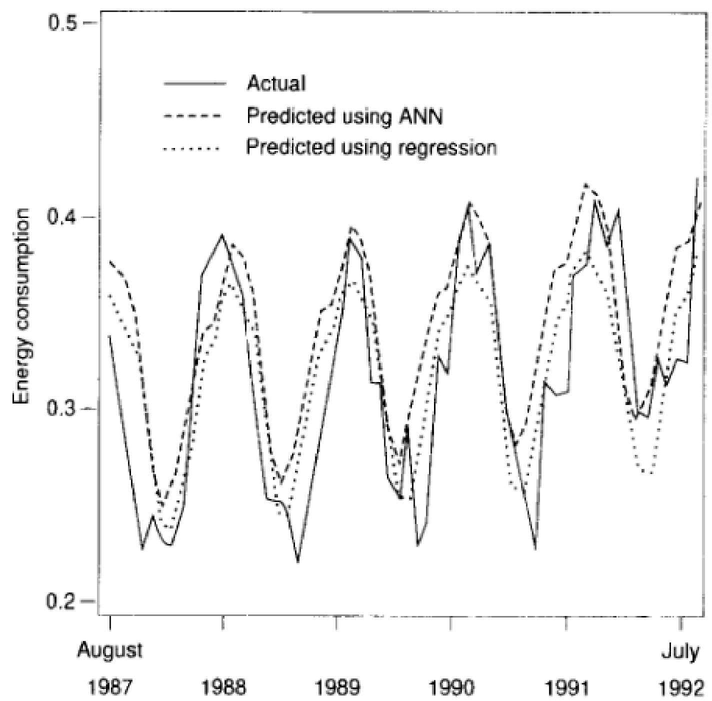



Figure 27- Comparison of predicted energy consumption using ANN and regression model [122]

The study concluded the advantage of ANNs over regression models and highlighted the capabilities of ANNs dealing with large datasets with little information regarding relationships between variables.

In the field of building energy consumption forecasting, the first found study was performed by Mozer [123], who used reinforcement learning to monitor a residential environment, infer patterns in occupant behaviour and needs and adjust building controls accordingly (Figure 28).

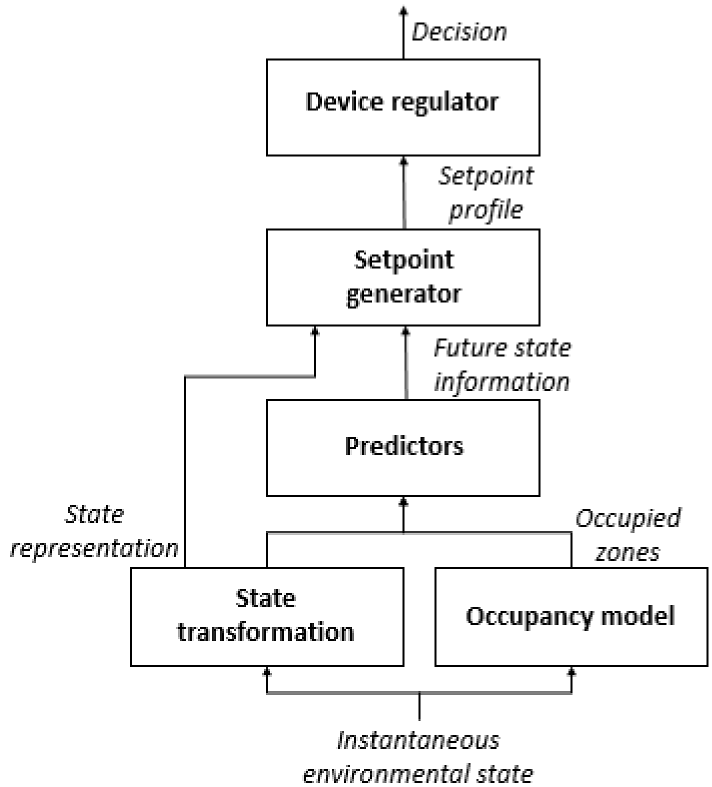



Figure 28- System architecture of the for determination of environmental state (figure reproduced from [123])

The system used an optimal control policy to reduce costs associated with occupant discomfort and energy. If occupants manually controlled the environment, the system used this as an indication of discomfort, and adjusted the optimum controls accordingly in order to reduce the need for manual control. The system also provided energy saving strategies by 'testing' occupants, setting control intensity lower than the believed optimal, and if the occupants did not show signs of discomfort, a new lower optimum setting threshold was set. The system was tested and outperformed simulation studies, however it was noted that long term testing was required to determine if there was enough regularities and patterns in occupant behaviour for suitable and robust training of the system to occur.

Likewise, in the area of energy control, Benedetti et al. [124] used ANNs to create an automatic energy consumption control system, in order to allow for easy maintenance and increased energy savings of a tertiary building. ANNs were trained using a large amount of data, but identifying such a vast amount of data is not always possible, therefore the authors developed a method of identifying a minimum dataset size which could obtain reliable results. The aim was to provide a method that could be adopted in any energy consuming system for maximum energy savings. The ANNs were trained using data in matrix form, organised using different time steps dependant on the energy collection system used. Monitored variables in the system included equipment, lighting, air conditioning, water pumps and boilers, lifts, external temperature, relative humidity and illuminance.

Afram et al. [125] used ANNs for a predictive control model to predict dynamic temperature set point profiles of the zone air and buffer tank water of a residential HVAC system in order to reduce operating costs without a compromise of thermal comfort. Such an approach was adopted as authors stated that minimisation of energy consumption was not an appropriate objective in the presence of variable energy prices, rather focus should be on the reduction of HVAC operating costs. However the implemented approach used more energy than when fixed HVAC set points were used, but resulted in lower operating costs due to its ability to store the energy in building mass during off peak hours.

Similarly, Chou and Bui [126] compared a number of prediction and data mining models including ANNs, regression trees and classification to predict heating and cooling loads of residential buildings, for use in the building design stage. Inputs to the model included building surface areas, glazing, orientation and compactness, which resulted a model with high accuracy for load prediction.

A number of authors have used both simulation and machine learning, for example, Neto and Fiorelli [127] utilised both simulation and ANNs to predict building energy consumption of a university building in São Paulo. Multiple models utilising different input parameters were tested, and it was found that humidity and radiation had very little effect on energy consumption in comparison to internal heat gains and equipment within the building. The ANN model outperformed the simulation model for energy predictions by 3%, however the study was classed as preliminary due to a large number of model uncertainties and simplifications. Naji et al. [128] also utilised simulation with ANNs, estimating residential building energy consumption based on building material thickness and their thermal insulation capability. The study concluded the importance of the technique for accurate estimation of building energy consumption during design and construction stages. Ekici and Aksoy [129] looked at building insulation thickness as well as building orientation for predication of building heating load using ANNs (Figure 29).

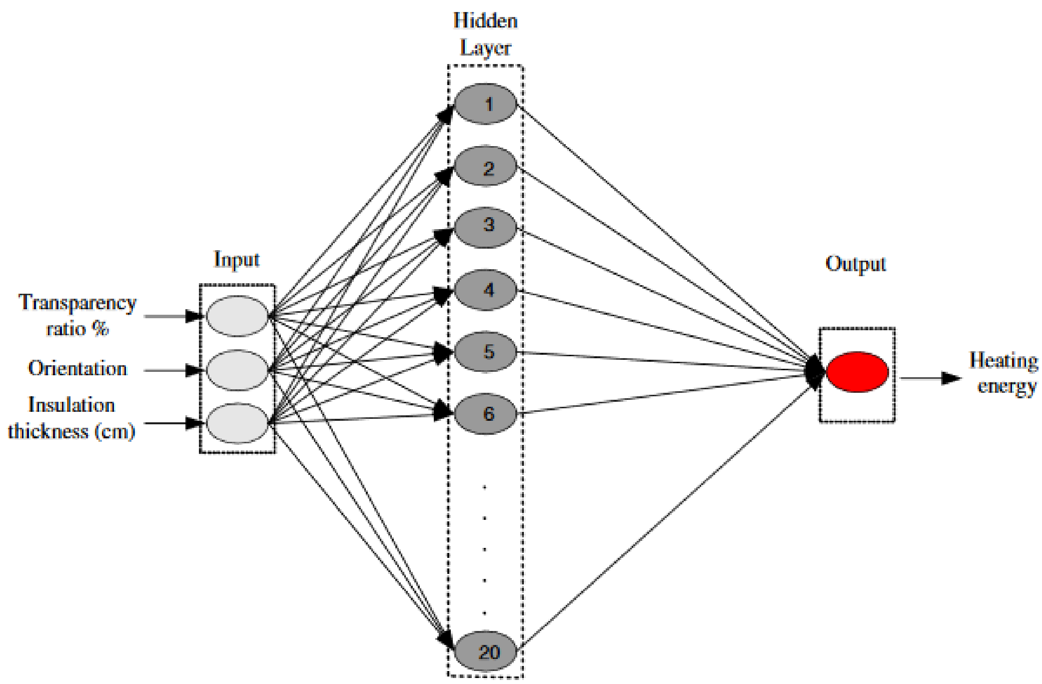



Figure 29- A three layered feedforward ANN [129]

The authors used ANNs along with computational energy calculations performed in FORTRAN, and achieved predictions to an accuracy of 94.8-98.5%, however stated that further work was required to include additional parameters such as lighting and cooling loads due to their influence on building energy efficiency.

Use of simulation and machine learning to optimise energy demand of a sporting facility whilst maintaining thermal comfort was performed by Petri et al. [130] where authors utilised a modular optimisation system in order to explore energy saving scenarios. The modular optimisation tool was tested on a sports facility in Rome, utilising data collected from sensors and actuators regarding consumption of electricity, gas, biomass, water and thermal energy as well occupancy levels. Predicted Mean Vote (PMV) was used to assess occupant thermal comfort. HVAC was analysed by assessing thermal and electrical energy consumption. The approach was able to provide significant electrical and thermal energy savings with control and uniformity over consumption intervals over the tested 42-day period. The tool provided a balance between optimisation objectives set such as HVAC set point, PMV, electrical and thermal energy consumption, energy savings and costs.

Vázquez-Canteli [131] coupled simulation with self-tuning control algorithms, deep reinforcement learning (DRL), for building energy management in the residential sector. CitySim building energy simulation software was used to compute heating, cooling and lighting energy demands at hourly intervals, with data passed between CitySim, the controller, and the deep neural network used for the DRL in a batch learning process. Two case studies were investigated, the first of which used DRL to minimize energy consumption of a heat pump, chilled water tank and photovoltaic array, the second of which looked at storing and releasing cooling energy from the chilled water tank for demand response analysis for two buildings. The use of DRL allowed the system to tune itself and adapt to sudden changes in the building characteristics, as well as being able to identify control policies identified after the learning process when the system was offline, using historical data, as well as online, when the system is being controlled. In both case studies, electrical energy costs were reduced, highlighting the potential for the use of DRL to find optimum control strategies and minimize energy consumption and costs in an adaptive manner. However communication between CitySim and the DRL program was challenging, with simulation speed depending on the controller and simulation itself, with the speed of the controller depending on batch sizes, model convergence, iterations and epochs. When multiple buildings were involved, as seen in a second case study, all buildings must have finished their commutations before simulation can advance and data could be exchanged with new actions taken, resulting in limited simulation speed.

Construction properties have also been used to predict energy consumption, heating and cooling loads of buildings during design stages. Khalil et al. [132] predicted heating and cooling loads of a building during its initial design stages based on compactness, areas of roofs, walls and glazing, height and building orientation.

A review of modelling and forecasting tools used for building energy consumption was performed by Suganthi and Samuel [133], and more recently Bourdeau et al. [113]

Amasyali [134] used deep neural networks (DNN) to predict cooling energy consumption of an office building based on outdoor weather conditions for 5 different climatic locations in the USA. The DNN was trained using a simulation-generated dataset including hourly cooling energy consumption levels and climatic data. Support vector machines, random forest and linear regression models were also developed as benchmark tools, trained using MATLAB. The predictions made by the DNN for hourly cooling energy consumption achieved good accuracy for all five locations tested, based on the CV and $R^2$ metrics, showing the potential for the use of DNN for building energy predictions.

Recurrent neural networks are a form of neural network used for processing sequential data with predictions based on both the current input and contextual information of previous inputs, making them highly suited to applications utilising sensor data. A number of studies have adopted their use for energy demand predictions, commonly outperforming other machine learning algorithms and statistical techniques, the most common form of recurrent neural network being a long short term memory (LSTM).

An LSTM coupled with an AutoEncoder for feature extraction proposed by Gensler [135] outperformed LSTM, deep belief network and multi-layer perception neural networks for solar power forecasting, wheras Bouktif [136] utilized LSTMs to forecast medium (few weeks to months) to short term (few days to two weeks) electrical loads. Electrical energy consumption data was merged with weather data and time lags, of which are known to influence power demand. Feature selection was used to adopt the best features for the model, and genetic algorithm to find the optimal number of time lags and layers in the model. The model outperformed other commonly used machine learning approaches (Linear, K-Nearest, Random Forest, Gradient Boosting, ANN, Extra Trees, Ridge) in the prediction of loads of a metropolitan area in France.

Likewise Mohammad [137] proposed a deep feed forward neural network (FNN) and a deep recurrent neural network (RNN) for energy load forecasting in smart grids (Figure 30).

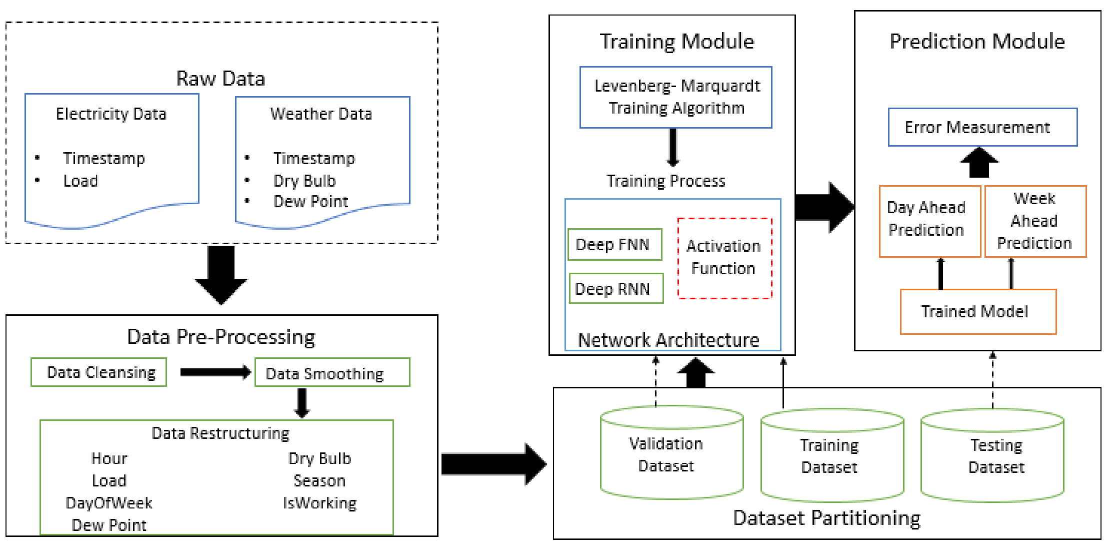



Figure 30- Energy load forecasting model (figure reproduced from [137])

Similar to Bouktif, the authors merged weather data and time effects with the energy consumption data to improve accuracy of the model. The deep RNN model outperformed the deep FNN model as well as the shallow neural network, ensemble tree bagger and linear regression models tested. Higher error was seen for predications in summer due to unexpected variations in electricity consumption resulting from high temperatures and social events. The model however is yet to be tested on real world datasets.

Although LSTM are commonly utilized for demand and load prediction, no studies were found utilizing such algorithms in the manufacturing sector or for HVAC system analysis.

In the field of indoor climate monitoring and HVAC analysis, in the energy sector, Ahmed et al. [138] used random forest along with other predictive modelling methods to predict useful hourly energy from thermal collector systems. The use of random forest models for building energy predictions has been performed by Wang et al. [139] and Smarra et al. [140], the latter of whom discussed heating system scheduling and thermal comfort requirements.

Ahmad et al. [141] used ANNs and random forest models to analyse hourly HVAC energy consumption of a hotel based on the input variables outdoor weather conditions, hour of day, month of year, number of guests and number of rooms booked. The authors concluded the models had comparable predictive power, were capable of non-linear mapping generalisation, and were nearly equally applicable and suitable for building energy predictions. Random forests however were able to handle missing values in datasets, and could accurately predict energy consumptions with missing output variables. Although less accurate results for the random forest were obtained, such results were within an acceptable range for HVAC energy consumption prediction purposes.

Banihashemi et al. [142] coupled ANNs with decision trees to develop a hybrid model allowing for both continuous and discrete parameters of energy consumption to be used simultaneously for the prediction of building energy demand. The dataset included information regarding the building envelope, building design layout and HVAC system. The model was able to resolve the issue of using both continuous and discrete parameters of energy whilst enhancing the accuracy of the objective functions used in building energy prediction and optimisation. However it was stated that the model may not be applicable to other types of machine learning algorithms, and more validation is required in other contexts using larger sample sizes covering various building energy parameters and climates.

### 2.6.3 Machine learning in manufacturing

Machine learning in manufacturing has been seen for fault detection [143], [144] and parameter investigation [145], [146], however studies on energy prediction and use of machine learning techniques in the manufacturing sector is limited, with a focus predominately on commercial or residential buildings.

Studies found on energy consumption in the industrial sector are discussed, however no studies were found regarding optimisation of HVAC systems in manufacturing nor the use of machine learning or predictive techniques for manufacturing HVAC systems.

In the manufacturing sector, Cupek et al. [147] presented a unsupervised iterative k-means clustering approach used to predict the energy consumption profile of compressed air systems for an automotive assembly station, in order to monitor energy efficiency and detect abnormalities. K-means finds patterns in datasets and was used to sort data into one of k groups. The method allowed energy consumption profiles specific to system states to be predicted based solely on behavioural observation and the classification of the production cycle, without need for data regarding control procedures executed by the production station (Figure 31).

Azadeh et al. [148] used ANNs for long term electrical energy forecasting in high energy consuming industrial environments, such as chemical, metal and mineral based industries. The authors predicted annual energy consumption based on electricity price, the number of electricity consumers, price of fossil fuels, electricity intensity and value added, and discussed the advantages of ANNs over regression techniques, such as the ability to handle data prone to fluctuations.

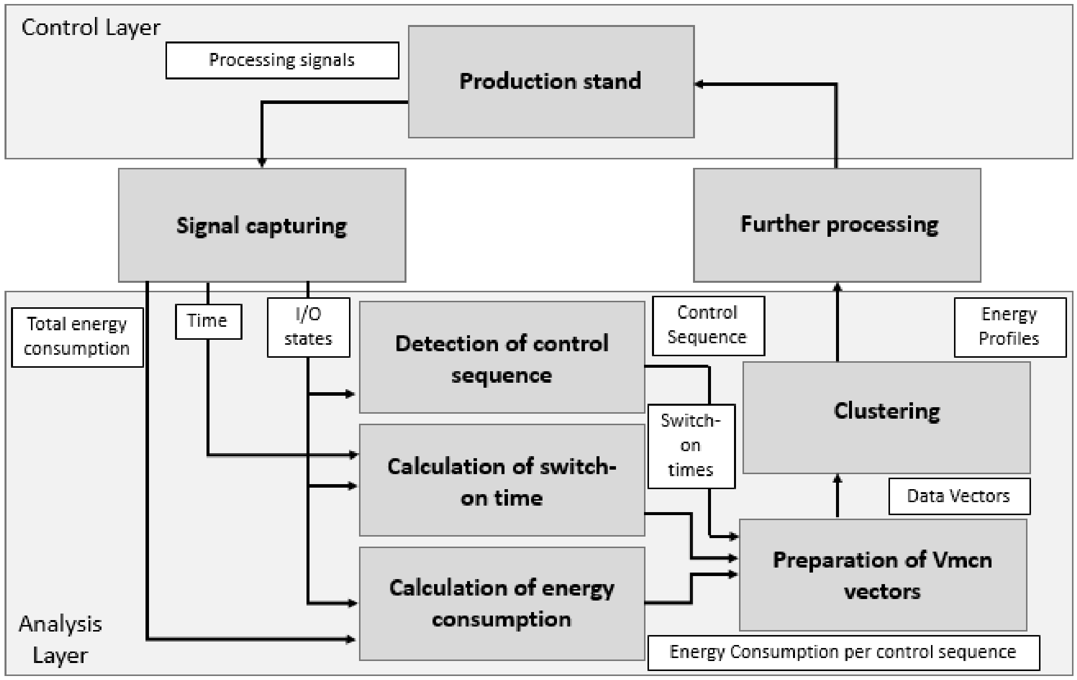



Figure 31- Method to determine energy consumption profiles (figure reproduced from [147])

Olanrewaju and Jimoh [119] discussed the development of a model integrating Index Decomposition Analysis, (determining factors responsible for energy consumption), Data Envelopment Analysis, (assessing energy saving potential), and ANNs to serve as a long term planning tool to ensure energy is available to meet demands of targeted economic growth in the industrial sector. The authors concluded by stating the importance of developing integrated models to analyse and assess energy efficiency potential in the industrial sector.

## 2.7 Research Gap

Very few studies have been found which investigate the impact of manufacturing demand on HVAC control or building energy, with any holistic simulation analysis tool merely existing as a planning framework or in discussion. Existing work performs such investigations through the use of DES tools, thus interdependencies between system and building level are neglected and the continuous parameter of energy flows is difficult to analyse. Likewise, little work has been done at investigating HVAC control in manufacturing environments. The use of predictive machine learning models in the industrial sector is limited, with no application to peak energy demand reduction, HVAC analysis or indoor climatic condition monitoring.

Upon achieving objectives specified in section 2.9, the aim of this research, '*Coupling Simulation with Machine Learning for the Development of a Proactive HVAC System in the Manufacturing Sector*' can be achieved in order to fill this research gap. The critical review of literature in this chapter achieves the first objective of this research.

## 2.8 Aims

In Chapter 2.7, a research gap was identified which emphasised a lack of investigation into the impact of manufacturing demand on HVAC control or building energy. Furthermore, little work has been done at investigating HVAC control in manufacturing environments or discuss use of predictive tools in the manufacturing sector for building energy optimisation or peak demand monitoring.

The research in this thesis therefore focuses on improving knowledge surrounding the effects of manufacturing demand on building energy consumption through holistic analysis of thermal energy flows and interactions between equipment, occupants, weather, the built environment and building control.

Through the coupling of simulation with machine learning, a novel predictive manufacturing based HVAC control strategy was developed in order to improve the energy efficiency of HVAC systems. Machine learning techniques can provide the automation of optimum HVAC controls, allowing for the continuous improvement of an intelligent HVAC control system.

Such an approach allows facility decisions to be made based upon extensive knowledge regarding energy flows within the building. Furthermore, the implementation of a proactive based HVAC system allows for the maintenance of comfortable working environmental conditions and also a reduction in operational costs, as well as allowing predictions of peak energy demand.

The overall aim of the research is therefore;

'*Coupling Simulation with Machine Learning for the Development of a Proactive HVAC System in the Manufacturing Sector*'.

## 2.9 Objectives

The following objectives were to be satisfied in order to achieve the research aim;

1. Conduct a critical review of literature in order to identify gaps in existing research and provide a focus for the research in this thesis.

2. Modelling of a manufacturing environment utilising simulation tools to analyse the link between manufacturing schedules, machining heat gains with building energy consumption and HVAC demand through a holistic energy analysis.

3. Determine effectiveness of the degree-day method for analysing manufacturing facilities.

4. Development of a proactive manufacturing HVAC control system, based upon upcoming manufacturing schedules and weather conditions as opposed to the traditional thermal comfort based system.

5. Implement the use of machine learning for prediction of optimum HVAC controls, along with prediction of indoor conditions to ensure an optimum thermal environment is maintained.

6. Implement the use of simulation and energy prediction for schedule optimisation of machining and HVAC to achieve a reduction in energy consumption spikes.

7. Production of a framework on the development of a manufacturing based HVAC system, utilising predicted optimum HVAC controls.

## 2.10 Summary of Literature

The main findings of the literature review are summarised below.

1. A common theme which is highlighted as being of upmost importance is the desire for increased knowledge surrounding energy use in the manufacturing and industrial sector. Knowledge and understanding of energy flows and the interaction between manufacturing and the building is essential. Without knowledge and willingness of workers, an energy plan is impossible to implement, and a company's energy saving potential will not be reached [17] [49].

2. In manufacturing, DES is a common tool for optimising and analysing scheduling, process planning and resource management due to its ability to model non-continuous processes and thus identify machine state behaviour and bottlenecks [33]–[36], [38]–[41][48]. Simulation is extensively utilised to determine associated energy of various tools and cutting parameters at tool level, being able to determine tool wear and related carbon emissions [52]–[56].

3. From a financial standpoint, in manufacturing management, energy is generally ignored and considered an indirect cost to production. Focus is predominately on improving profits and productivity. However energy saving strategies are triggering industrial companies to look at their peak energy consumption, of which can be responsible for 30% of their total monthly operating cost [47], [65], [149].

4. Industry 4.0 brings a large increase in interconnected systems and data streams, with the potential to utilise this data for efficient planning, resource allocation, energy analysis, predictive machine maintenance, connected machining, processes, logistics and services. However barriers to knowledge gain are the need for specialist data collection systems, processing, analytical and storage tools, as well as knowledge

[82]. Furthermore, such data is predominately utilised for improvements in profits, resource allocation and product throughput [81].

5. The importance of analysing the building shell alongside manufacturing processes is highlighted due to the interdependency between equipment, occupants, building fabrics and TBS. Efforts to combine manufacturing energy flows with that of the building have been performed, with 71% using DES, tools which combined DES with continuous approaches were used for 16% of studies [83].

6. After process heat generation, the largest energy consumer in manufacturing facilities are the demands from HVAC systems and lighting [108], however the control and energy requirements of systems are often neglected in manufacturing facility analysis. Conflicts exist in literature of whether manufacturing schedules are considered to have an impact on the energy consumption of non-production related energy consumers such as HVAC and lighting. Katunsky et al. [87] stress the importance of machines on HVAC system energy consumption, whereas Gahm et al. [64] state that climate control is not influenced by machine scheduling.

No studies were found to analyse the use of machine heat generation for space heating, nor analyse or discuss its effect on HVAC operation or building control and energy demand.

7. Due to the simplicity of statistical regression models, most regression techniques are unable to deal with the nonlinear behaviour of energy use and efficiency in buildings [113]. Models lack flexibility and require a large amount of data to draw any significant conclusions and relationships between data. Alternatively, artificial neural networks are the most common predictive technique in the energy sector, being used for building energy prediction, district and countrywide energy prediction, heating demand and renewable energy efficiency predictions.

8. In the residential and commercial building sector, machine learning techniques have been applied to HVAC systems as well as being utilised for heating and building energy predictions [122]–[126], [132], [134], [141], with few studies coupling machine learning methods with simulation [127]–[131]. In the manufacturing sector, machine

learning has predominately been utilised for fault detection and machine parameter investigation with few studies found on facility energy consumption [143]–[146].

9. Investigations into reducing peak energy demand of a manufacturing facility have been performed, however such work has been done looking at altering machine schedules, rather than working with both the manufacturing schedules and building behaviour as a whole.

10. Use of degree-days in building energy analysis has been criticised due to its questionable accuracy, however little work has been done looking at the applicability of degree-days to manufacturing building energy analysis.

# Chapter 3- Simulation Modelling

## 3.1 Introduction

This chapter discusses the modelling of a manufacturing environment using simulation. Software use justification in section 3.2 is preceded by theory behind the modelling tool utilised. A case study is introduced in section 3.4, along with model boundary conditions and discussion on the type of case study used. The final section, 3.5, introduces various HVAC control systems.

## 3.2 Simulation Theory & Software Justification

### 3.2.1 Simulation Theory

Computational simulation is a popular methodology for analysis of building energy systems, and thus there are many commercial simulation tools available such as DOE [150], EnergyPlus [16], ESP-r [19], TRNSYS [20] and IES-VE [18].

Energy models are classed as white, black or grey box approaches. A white box model uses specified input variables to a model in order to predict output variables. TRANSYS, DOE, EnergyPlus and ESP-r work on these principles. A grey box approach uses a physical model from which important parameters and characteristics are determined by statistical analysis, however such an approach is unsuitable for whole building analysis, rather is suited to fault detection and diagnosis [3]. Black box approaches use a model structure estimated by variable regression analysis between input variables and measured output variables of energy consumption. However for long term simulations, the resultant model bears negligible physical resemblance [3].

### 3.2.2 Software Justification

IES-VE was selected as the simulation tool in this study. IES-VE is a time-series driven simulation tool used for modelling of thermal energy flows of a building shell. IES-VE encompasses a number of modules to determine the impact of certain parameters on building energy flows. A SunCast module is utilised for analysis of weather conditions and solar gains, MacroFlo for natural ventilation analysis, Apache is provided for thermal analysis, ApacheHVAC for HVAC system implementation, ModelIT for geometry definition with results of simulations concluded in VistaPro. Furthermore, a Component module allows for the placement of furniture or electrical items such as radiators and ovens.

Although a number of building simulation tools were available, IES-VE was utilised in this study due to its availability and reputation, as well as the provision of the Component tool. A manufacturing add on was available as part of the component module, which allowed for modelling and placement of manufacturing equipment within the building. Parameters such as process materials, grades and flow rates can be specified, as well as energy inputs to a machine, energy outputs, per product energy generation, sensible and latent heat output as well as product outputs. Furthermore, energy meters could be set up specific to individual machining processes, and allowed for grouping of processes or individual analysis of energy, waste heat and product generation. Thus, the tool allowed for analysis of the facility alongside the manufacturing processes.

#### 3.2.2.1 Energy Flows

IES-VE is based on the first principles of heat transfer. Although IES-VE is a time series based modelling software, its ApacheSim module used for modelling thermal characteristics, can be classed as a dynamic model according to the Chartered Institution of Building Services Engineers (CIBSE) model classification. ApacheSim addresses [18];

- Thermal insulation (type and placement)
- Building dynamics & thermal mass
- Building configuration and orientation
- Climate
- Glazing properties
- Shading, solar gain & solar penetration
- Casual gains
- Air-tightness

- Natural ventilation
- Mechanical ventilation
- HVAC systems
- Mixed-mode systems

IES-VE performs heat loss and heat gain calculations based on the principles stated by CIBSE, whereas heating and cooling load calculations are performed according to the ASHRAE Heat Balance Method. The Heat Balance Method used by IES-VE calculates radiative delay effects within the building explicitly, by specification of assumptions on surface temperatures.

Energy transfer processes within a building space of which is conditioned by a HVAC system, and thus requiring thermal analysis within the simulation model, is displayed in Figure 32.

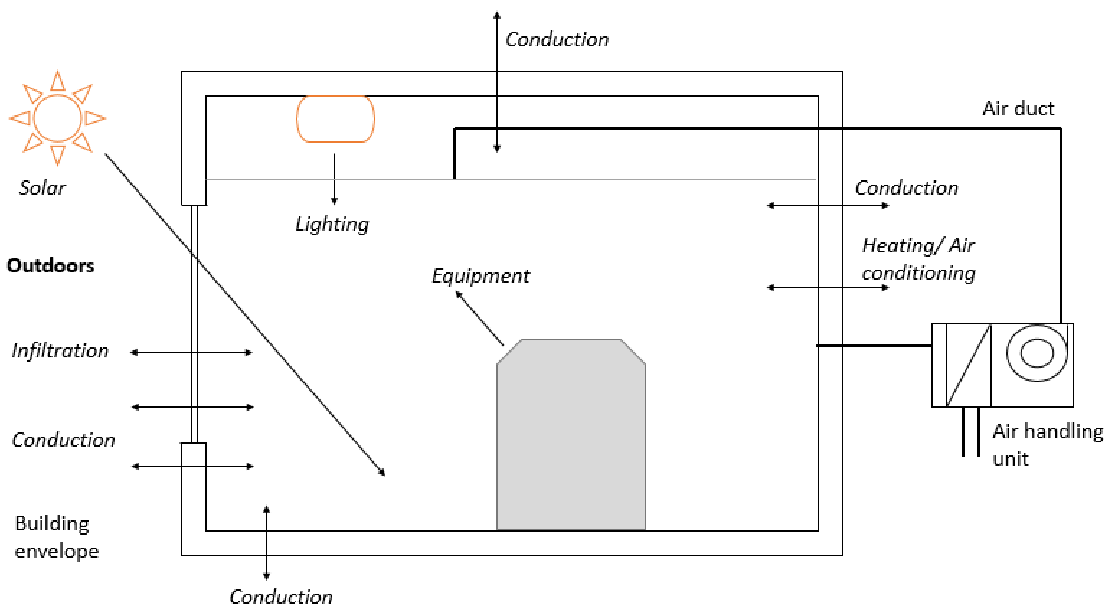



Figure 32- Energy transfer processes taking place within a building space conditioned by a HVAC system (figure reproduced from [200])

IES-VE adopts a finite difference approach, where elements are represented by nodes, a point at which thermal calculations are performed. Calculations at each node are performed at each user specified time step, with the number of nodes determined by the simulation model resolution.

Heat flow through a building is often analysed using a network model, and although energy flows in reality is a continuum, the network model provides a successful approach to thermal building simulation (Figure 33 and Figure 34). The electrical network model consists of time dependant resistance and capacitance, with electrical current flowing in each branch of the network equivalent to the thermal energy flows between building elements and stochastic thermal inputs from sources such as occupants, HVAC, manufacturing equipment and solar gains. Each node can be thought of as having different capacitance.

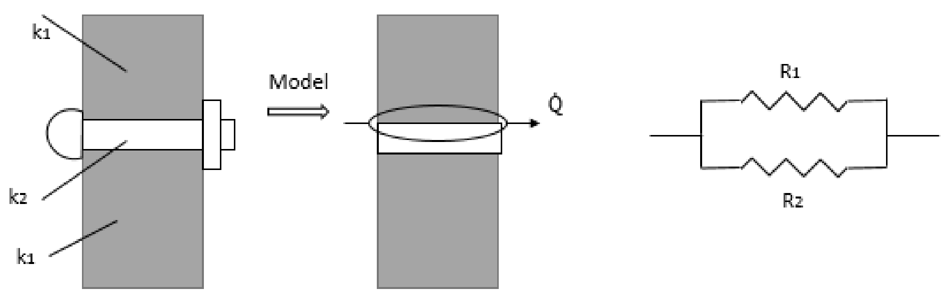



Figure 33- Electrical network model for thermal energy transfer in buildings- heat transfer for a wall with dissimilar materials ( Figure reproduced from [201]), where $k_n$ is thermal conductivity ($W$ m$^{-1}$ $K^{-1}$), $\dot{Q}$ is the rate of heat transfer ($W$) and $R_n$ is thermal resistance

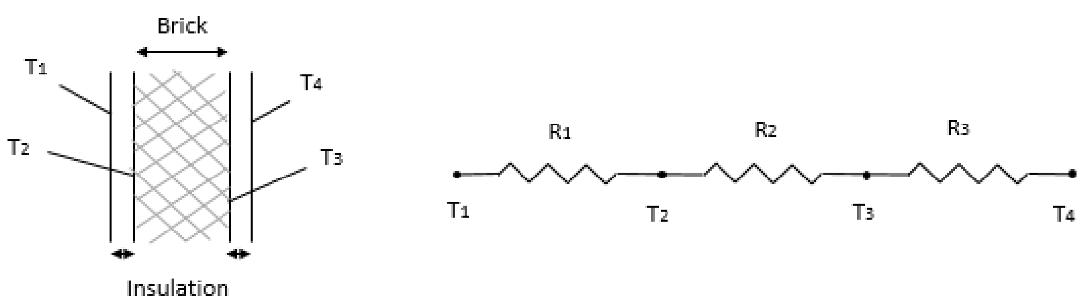



Figure 34- Electrical network model for thermal energy transfer in buildings- heat transfer through an insulated wall (figure reproduced from [201]), where T is surface temperature (K)

Flow paths can be represented as a single path, with flow from a cooler to a warmer space, or as a flow of energy across many layers in series or parallel. These layers act as resistance to the flow of thermal energy, and therefore transmission of heat through a building can be considered as a network of resistances in series (Figure 35) or parallel, where the thermal resistance, R ($W^{-1}$ $m^2$ $K$), is determined based upon the elements thermal conductivity, $k_t$ ($W$ $m^{-1}$ $K^{-1}$), and thickness, x (m) (Equation 4 ). A high R value is desirable in order to reduce heat loss.

$$R = \frac{x}{k_t}$$

Equation 4- Thermal Resistance [151]

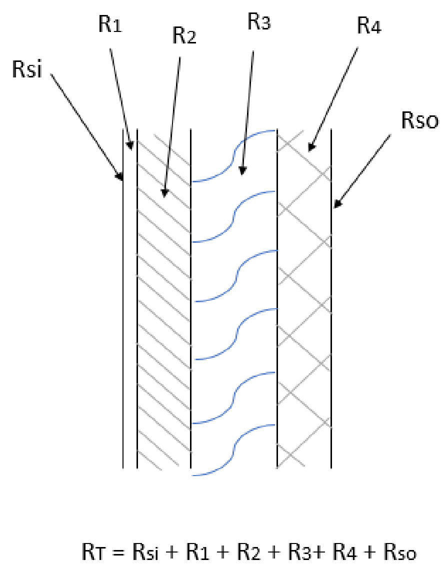



Figure 35- Thermal resistance across a boundary

This thermal transmittance is known as the U value ($W$ $m^{-2}$ $K^{-1}$), expressing heat transmittance through a piece of material due to a temperature difference (Equation 5).

$$U = \frac{1}{R}$$

Equation 5- Thermal Transmittance [151]

The lower the U value, the more insulated the building will be. However poorly fitted insulation, gaps and bridges between partitions or building fabrics can increase a U value.

#### 3.2.2.2 Thermal Bridging

In buildings, thermal transmittance is not consistent across the entire wall area. A thermal bridge is considered to be an area where thermal transmittance is higher, and results in a higher rate of conductive heat loss than that of the wall. Thermal bridges arise at a break in insulation, window seals, gaps in the walls for piping and cables as well as junctions between walls and flooring.

An allowance for non-repeating thermal bridging can be made in IES-VE, by the addition of 10% to the U value.

## 3.3 Heat Transfer by air movement

A building is subject to air exchanges due to infiltration and air gaps in a building shell, natural ventilation, for example window opening, and mechanical ventilation from air exchange units and HVAC systems. Both MacroFlo and ApacheHVAC work alongside ApacheSim for the analysis of air flows due to natural ventilation and buoyancy flows, as well as from HVAC systems. The rate of heat transfer associated with a stream of air entering a space, $\dot{Q}$ (W), is determined by Equation 6.

$$\dot{Q} = \dot{m}c_p(T - T_a)$$

Equation 6- Rate of heat transfer associated with air entering a space ([152])

Where $\dot{m}$ is the mass flow rate ($kg\ s^{-1}$), $c_p$ the specific heat capacity ($J\ kg^{-1}\ K^{-1}$), T is the supply temperature of air (K) and Ta is the mean air temperature (K).

The $CO_2$ concentration of outside air is assumed to be a constant, whereas $CO_2$ gains in indoor spaces is calculated based upon $CO_2$ levels of the indoor air and of the supply air, as well as upon sensible and latent heat gains of occupants within the space.

Buildings are subject to ventilation and air exchange, of which is required for a reduction in harmful pollutants and water vapour and to provide a fresh air supply for occupants. Ventilation in excess however can increase heat loss, therefore a balance between clean air requirements and heat loss is required. Heat loss due to air exchange is determined by Equation 7.

$$Q_{vent} = \rho VC\ (T_i - T_o)$$

Equation 7- Heat loss due to air exchanges ([152])

Where ρ is the density of air (kg $m^{-3}$), V the infiltration rate ($m^3$ $s^{-1}$), C the specific heat capacity of air (kJ $kg^{-1}$ $k^{-1}$) and $T_i$ and $T_o$ the indoor and outdoor temperatures (K) respectively.

### 3.3.1 Heat Conduction

Cengel and Boles define conduction as the transfer of energy from a more energetic particle to an adjacent less energetic one as a result of particle interaction [152]. The rate of heat conduction $\dot{Q}_{cond}$ (W) through a layer of constant thickness Δx (m) is proportional to the temperature difference ΔT (K) across the layer and the area A ($m^2$) normal to the direction of heat transfer, and is inversely proportional to the thickness of the layer (Equation 8). $K_t$ is the thermal conductivity of the material ($Wm^{-1}K^{-1}$), and specifies the ability of a material to conduct heat.

$$\dot{Q}_{cond} = \ k_t A \frac{\Delta T}{\Delta x}$$

Equation 8- Rate of Heat Conduction ([152])

Therefore utilising Equation 4 and Equation 5, in buildings, the heat transfer through an element of surface area A such as a wall can be defined by Equation 9.

$$\dot{Q}_{cond} = UA(T_i - T_o)$$

Equation 9- Conduction through a wall ([151])

Where $T_i$ and $T_o$ are the indoor and outdoor temperatures (K) respectively.

In IES-VE, the thermo-physical properties of building elements such as the density, specific heat capacity and conductivity of each layer is assumed to be uniform within each layer. Air gaps are also modelled as pure resistances.

### 3.3.2 Convection

Cengel and Boles define convection as the mode of energy transfer between a solid and an adjacent liquid or gas in motion [152]. In the absence of motion, the heat transfer between the mediums is pure conduction [152]. The rate of heat transfer, $\dot{Q}_{conv}$ (W), is determined by Newtons law of cooling (Equation 10);

$$\dot{Q}_{conv} = hA(T_s - T_f)$$

Equation 10- Newtons Law of Cooling ([152])

Where A is the surface area through which heat transfer occurs ($m^2$), $T_s$ is the surface temperature (K), $T_f$ is the fluid temperature (K) away from the surface and h is the convection heat transfer coefficient ($W\ m^{-2}\ K^{-1}$), calculated dependent upon variables such as surface geometry, nature of fluid motion, properties of the fluid and fluid velocity, of which are calculated iteratively. For example, for external forced convection, a wind speed dependant convective heat transfer coefficient is used, and is calculated based upon McAdams empirical equations, based upon weather data provided in the IES-VE weather files (Equation 11).

$$h = 5.6 + 4.0\,v \qquad (v < 4.88)$$

$$h = 7.2\,v^{0.78} \qquad (v \geq 4.88)$$

Equation 11- McAdams wind speed dependent convective heat transfer coefficients ([153])

Where v is wind speed ($m\ s^{-1}$).

### 3.3.3 Radiation

Radiation is the energy emitted by matter in the form of electromagnetic waves (photons) as a result of the changes in the electronic configuration of the atoms or molecules. Such a mechanism does not require medium between the two elements [152]. The radiation emitted from a 'real' surface, $\dot{Q}_{emit}$ (W), is expressed as stated in Equation 12.

$$\dot{Q}_{emit} = \varepsilon\sigma A T_s^4$$

Equation 12- Emitted Radiation ([152])

Where ε is emissivity of a surface, σ is a constant ($5.67 \times 10^{-8}\ W\ m^{-2}\ K^{-4}$), A is surface area ($m^2$) and $T_s$ is surface temperature (K). Emissivity ranges from 0 - 1 and determines how closely a surface represents a blackbody, an idealised surface emitting radiation at maximum rate. The net heat transfer between two surfaces is determined by Equation 13.

$$\dot{Q}_{rad} = \varepsilon\sigma A(T_s^4 - T_{surr}^4)$$

Equation 13- Net Radiative Heat Transfer ([152])

where A is the area of surface ($m^2$) at temperature $T_s$ and $T_{surr}$ is the temperature (K) of the surrounding surface. IES-VE adopts the mean radiant temperature model [154], which assumes the emissivity of the surfaces bounding a volume do not differ greatly from one another, which is commonly the case and allows for easier computation.

Water vapour in a room's atmosphere impacts air emissivity, therefore impacting radiant exchanges with building spaces. Humidity level regulation in a building space is critical for occupant thermal comfort, and in the case of a manufacturing facility, large pieces of equipment greatly influence such a balance. IES-VE models the effect of air emissivity due to water vapour adopting the model of Hottel (Equation 14) [155], where $p_w$ is the partial vapour pressure of the gas (Pa) and $L_e$ is the length of a gas mass (m).

$$\ln(\varepsilon_{air}) = -0.619 - (2.958 - 0.2184\ln(p_w - L_e))^2$$

Equation 14- Model of air radiant exchanges ([153])

#### 3.3.3.1 Solar Radiation

Thermal radiation in a human environment, such as in a building, is typically longwave radiation, whereas solar radiation is considered short wavelength, and is therefore calculated separately. ApacheSim calculates solar flux on each building surface, accounting for solar shading due to solar location and construction based shading devices. Dependent upon external conditions, solar radiation can raise exposed surface temperatures as much as 15-20 °C above ambient temperature and can directly contribute to changes in internal conditions. Along with direct solar radiation, atmospheric scatter and terrain reflection can also impact thermal conditions within the building space [156]. Cloud cover and solar attitude and azimuth were provided in the IES-VE weather files, whereas building location and altitude were specified upon model creation, along with solar shading devices.

## 3.4 Case Study

The framework for the approach used in this study is shown in Figure 36.

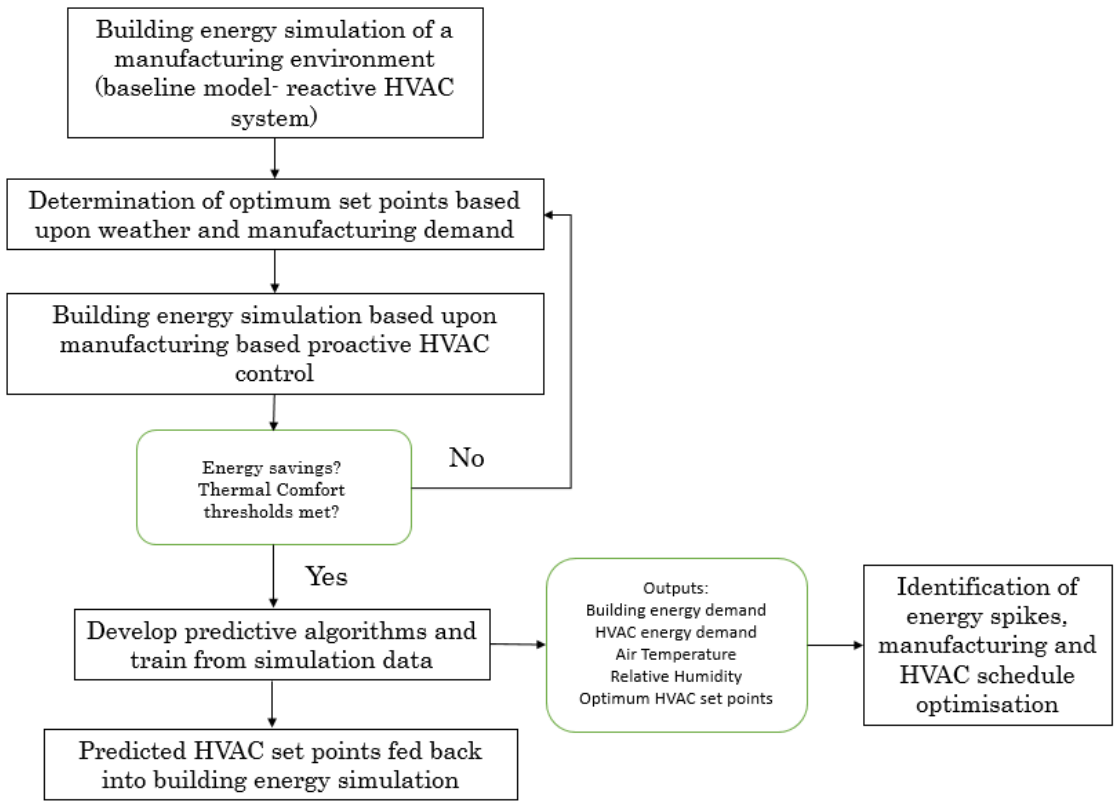



Figure 36- Study methodology

The first step in this study was the development of a baseline simulation model, which defines minimum energy performance. The ASHRAE Guidelines for measurement of energy and demand savings advises a baseline simulating period of 12 months in order to ensure that a certain month is not over represented in the final dataset [157]. Thus a simulation period of 12 months was used in this study. Furthermore, the use of a 12-month simulating period provided insight into the performance of the facility with energy savings measuring in differing seasonal climates.

Building simulation studies commonly use a time step of 60 minutes [158], however for shorter simulation periods (weeks or months) Albatayneh et al. [159] suggest the use of shorter time steps. Due to a simulation period of 12 months in this study, a time step of 10 minutes was used, with a 60-minute reporting interval.

### 3.4.1 Data Collection

In this thesis, a case study was used to test the proposed methodology. Manufacturing facilities are complex environments, with size, functionality, requirements and use varying across the sector, and therefore there is no blueprint for a standard manufacturing facility. Therefore, a generalized case study environment was utilised to test the proposed methodology, based upon data obtained from a number of manufacturing facilities and boundary conditions specified in literature, in order to determine a general case of an average facility (see Appendix A for further details). A review of literature collated 13 studies, [34], [71], [87], [88], [93], [96], [98], [102], [109], [160]–[163] , based on the energy analysis of manufacturing environments, providing a set of data including facility location, size, building energy and machining energy consumption, operational schedule, room conditions, machine types, HVAC operation and employee numbers. Not all variables were available for all studies, therefore based upon existing data, mathematical relationships were determined between existing variables in order to fill missing gaps in data. After data collation, a generalised dataset was produced in order to build a simulation model based on the 13 collated studies, including facility floor area, occupancy numbers, building energy consumption, machine energy consumption and number of machines, as well as trends into HVAC operation and room conditions (Table 1). HVAC operation was set based on thermal comfort, with 100% operation during working hours, as well as shortly prior to and after. HVAC systems were set to a reduced level of operation outside of the hours 7am- 6pm, as specified in analysed studies.

Table 1- Extrapolated Dataset

| Facility Size ($m^2$) | Occupancy (no of people) | Energy Consumption Estimate (MWh/yr) | Energy Consumption of Machines (MWh/yr) | Machining Schedule | Lighting (W $m^{-2}$) |
|---|---|---|---|---|---|
| 52407 | 1601 | 38795 | 24783 | Monday-Friday 9am-5pm | 6 |

However categorical variables such as building location could not be collated, and due to the dependence of building energy consumption on outdoor weather conditions, the manufacturing facility was simulated in 4 locations found in the studies for a period of one year (Table 2).

Table 2- Location data for modelled facility environments

| Location | Latitude (°) | Longitude (°) | Elevation (m) | Annual Dry Bulb Temperature Range (° C) |
|---|---|---|---|---|
| London, UK | 51.48 N | 0.45 W | 25 | 8.40 - 31.40 |
| Ulyanovsk, Russia | 54.32 N | 48.33 E | 127 | -4.80 – 34.90 |
| Munich, Germany | 48.13 N | 11.55 E | 520 | 7.10 - 32.90 |
| Chicago, Illinois, USA | 41.99 N | 87.91 W | 205 | 6.20 – 35.70 |

The facility was modelled without and with equipment, Figure 37 and Figure 38 respectively, to determine the impact of manufacturing equipment on the energy consumption trends of the facility and determine to what extent both internal gains of equipment and equipment energy consumption impact the seasonal trend of total facility energy consumption.

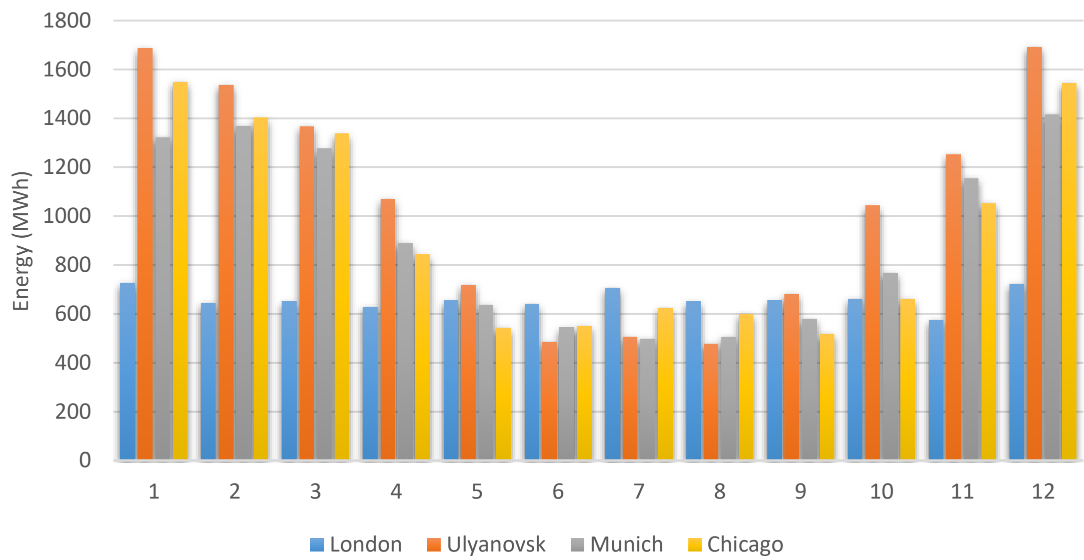



Figure 37- Annual Energy Consumption for the facility in 4 locations without manufacturing equipment present

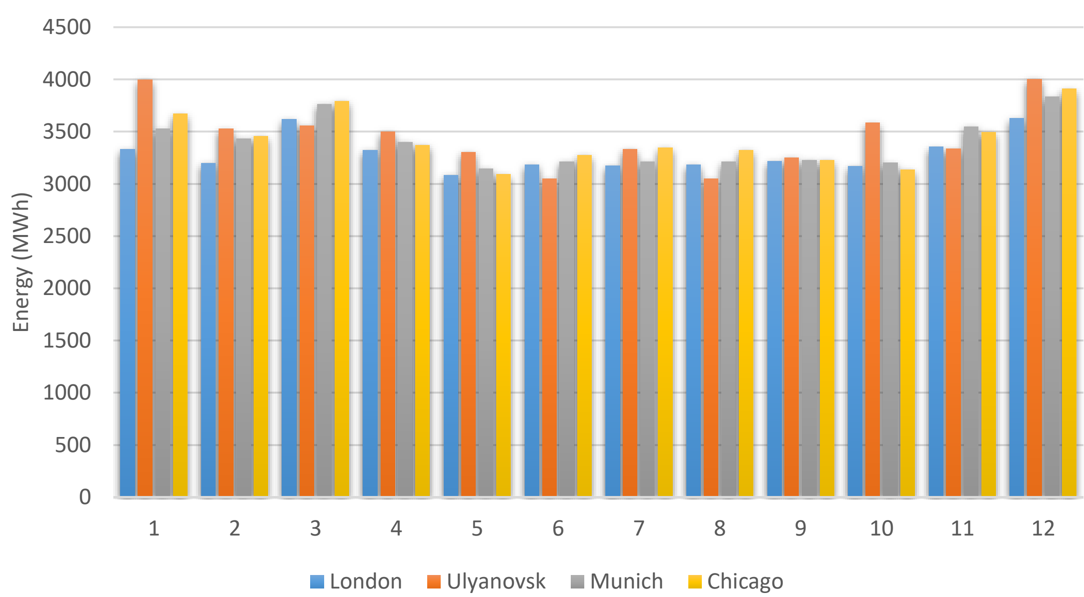



Figure 38- Annual Energy Consumption for the facility in 4 locations with manufacturing equipment present

As displayed in Figure 37, outdoor weather conditions has a substantial impact on the energy consumption HVAC systems, determining required heating and cooling energy demands. Building energy consumption for all four locations varied with a seasonal profile, requiring more energy in winter due to additional heating requirements. Such a trend is considerable for the building in Ulyanovsk and Chicago, locations which experience a large annual range of climatic conditions and temperatures, less so for London, of which experiences a much smaller annual temperature variation.

However when manufacturing equipment and internal heat gains were modelled within the facility, this seasonal trend was less, if at all apparent (Figure 38). The largest monthly energy fluctuation was a 31% difference between the lowest and highest monthly consumption, comparatively the fluctuation for the same facility without equipment was 255 %.

All four locations required a similar amount of energy to run the facility year round, due to the requirement for space heating in winter and space cooling in the summer due to manufacturing equipment heat gains. Requirements for the boiler system and cooling system followed a similar seasonal trend for all four locations (See Appendix B for further information), however total consumption for the building did not show such a trend.

In order to determine the extent to which outdoor weather conditions impacts the energy consumption of a manufacturing facility, and thus determine the importance of location in the generalised case study, Spearmans rank correlation coefficients (SCC) between energy consumption and outdoor temperature was determined for each manufacturing facility. Furthermore, the SCC for the relationship between manufacturing demand and building energy consumption was calculated, in order to identify the extent to which manufacturing schedules impact final energy consumption of the facility in comparison to temperature.

The SCC is used to determine monotonic associations between two quantitative variables, and ranges from -1 to 1 denoting a negative and positive correlation respectively. With a monotonic relationship, variables under analysis change together, but not necessarily at a constant rate, as opposed to a linear relationship, where one variable changes proportional to the next.

A correlation coefficient of zero indicates no relationship between variables. SCC (Equation 15), requires variables to be ranked in size order prior to analysis.

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Equation 15- Spearman Correlation Coefficient [164]

Where n is the sample size and d the difference between the two ranked variables for analysis at index *i*,.

The SCC was performed on an hourly basis for all locations. Table 3 displays the SCCs for analysis of building energy consumption with outdoor temperature and building energy consumption with manufacturing demand over a one-year period for a facility with equipment.

Table 3- Spearman Correlation Coefficients for building energy consumption vs outdoor air temperature and building energy consumption vs manufacturing demand for a facility building with manufacturing equipment

| **Location** | **SCC** | |
|---|---|---|
| | **Energy vs Temperature** | **Energy vs Manufacturing** |
| **London** | -0.12 | 0.755 |
| **Ulyanovsk** | -0.14 | 0.755 |
| **Munich** | -0.09 | 0.756 |
| **Chicago** | -0.13 | 0.755 |

The relationship between building energy consumption and outdoor temperature was weak for all locations, indicated by a SCC of -0.1 for all locations. However the relationship between building energy consumption and manufacturing schedule was significant, a SCC of above 0.75, indicating that for manufacturing facilities the presence of manufacturing equipment is much more influential on building energy consumption than outdoor weather conditions.

Due to the low relationship between outdoor temperature and building energy displayed in and Table 3, along with the limited seasonal fluctuation in energy consumption displayed in Figure 37, it was concluded that the use of a generalised dataset adopting literature data from facilities worldwide was suitable for the methodology adopted in this study. Such a method provides a larger dataset to extrapolate from in order to build the case study dataset, and therefore provide a model that is more representative of a real manufacturing facility. As focus in this thesis is the relationship between energy consumption and manufacturing demand and schedules, the chosen data selection methodology was justified. Furthermore, the use of historical data in such a format provides a pre-validated dataset for use in the study. The model in this study utilised suburban London as a default location for all simulations.

The case study data was also used to determine the suitability of the degree-day method for analysis of manufacturing facilities. The SCC between degree-days and energy consumption, as well as manufacturing schedule and energy consumption was determined for all four locations. Furthermore, the SCC between degree-days and HVAC energy was determined, along with manufacturing demand vs HVAC energy to determine the relationship between degree-days and HVAC energy for a manufacturing environment.

### 3.4.2 Boundary Conditions

#### 3.4.2.1 Casual heat gains

Causal Heat gains within the space included computers in office space, lighting, people and manufacturing equipment. The internal gains are composed of a sensible and latent component. Latent heat is associated with a phase change, such as addition of moisture to the space due to evaporation, and are considered instantaneous loads [165]. Sensible heat is the energy associated with a temperature change with no phase change, and can result from conduction, convection and or radiation.

Occupants lose heat both by latent heat, due to respiration or sweating, and also sensible heat, for example heat release due to the higher temperature of the skin with respect to the environment. Likewise, lighting provides a means of sensible internal heat, where radiative energy is emitted to the space only after it has been absorbed by room surfaces. Electrical plug loads provide sensible heat gain only, however equipment such as cookers provide both sensible and latent heat gains.

The radiant fraction is used to characterise the amount of radiant heat given off from an object, the remainder of heat dissipation being convective. The convective heat is transferred to the surroundings instantaneously, whereas the radiative heat is absorbed by room surfaces and dissipated over time [166]. A value of 0.0 to 1.0 is used to characterise the amount of radiative heat released, with a value of 0.0 indicating solely convective heat gains to the environment, and 1.0 indicating purely radiative gain. The convective component is directly transferred as energy gain to the room, whereas the radiative part is distributed to surrounding surfaces.

Internal gains for the space were referenced from CIBSE Guide A [167], and referenced in Table 4.

Table 4- Internal Gains for the Facility

| Type | Sensible Gain | Latent Gain | Radiant Fraction |
|---|---|---|---|
| **People** | 75 W / person | 55 W / person | 0.20 |
| **Lighting** | 6 W $m^{-2}$ | - | 0.45 |
| **Computers** | 11000 W | - | 0.22 |
| **Manufacturing Equipment** | 20% of machine load | | 0.1 |

Occupants were set to be distributed with a density of 32 $m^2$ / person based on data in Table 1. The diversity factor which account for the percentage of computer equipment being idle or turned off can vary from 37-78% [167], thus the heat gains specified from computer equipment was set to match an average computational use.

Due to the method of data collection in this study, individual machine data was not known. Therefore, the methodology adopted by Katunksy et al. [87] in which machines are modelled as black boxes detailed by electrical power and dissipated thermal energies, was utilised. The Verein Deutscher Ingenieure (VDI), an association of German engineers setting standards in engineering, Standard 3082 state that a value of 15% – 20% of the installed machine load is released as heat gains to the surrounding environment [168]. Weeber et al. further confirmed the use of 20% of machine load in his study of energy efficiency in factories [88], and was thus used in this study.

The radiant fraction for manufacturing equipment was unknown however a typical value is between 0.1 and 0.5 [169].

In order to determine the effect of the radiant fraction on HVAC system energy, a number of radiant fractions were analysed for a period of one year (Table 5).

Table 5- Manufacturing equipment radiant fraction investigation

| **Radiant Fraction** | **HVAC System Energy (kW)** |
|---|---|
| **0.1** | 17854.07 |
| **0.3** | 17833.07 |
| **0.5** | 17812.11 |

Error between the highest and lowest obtained HVAC system energy consumption was deemed negligible at 0.24%. Therefore, a radiant fraction of 0.1 was used for the manufacturing equipment throughout all simulations.

#### 3.4.2.2 Construction Materials

Building construction materials are highly location dependant, with different climates requiring different levels of insulation, rain and wind protection. As the facility was modelled in London, UK-based industrial construction material recommendations were utilised to build the simulation model [170] (Table 6).

Table 6- Building Model Construction Parameters

| **Description** | **Materials** | **U value ( W $m^{-2}$ $K^{-1}$)** |
|---|---|---|
| **Internal Ceiling/ Floor** | Chipboard- 30mm, SCREED- 170mm, Reinforced Concrete- 170mm, Cavity- 50mm, Plasterboard- 10mm | 1.10 |
| **External Door** | Steel- 30.4mm | 5.86 |
| **Internal Door** | Plywood- 30mm | 2.20 |
| **External Window** | Outer Pane- 6mm, Cavity- 12mm, Inner Pane- 6mm | 1.60 |
| **Exposed Floor** | Insulation- 98.2mm, Reinforced Concrete- 100mm, Cavity- 50mm, Chipboard- 20mm | 0.22 |
| **Internal Partition** | Plasterboard- 12.5mm, Cavity-50mm, Plasterboard-12.5mm | 1.79 |
| **Roof** | Asphalt Roofing-30mm, Membrane- 400mm, Insulation- 100mm, Steel- 30mm | 0.23 |
| **External Wall** | Rainscreen-3mm, Cavity-50mm, Insulation- 80mm, Cement Particle Board- 12mm, Cavity- 50mm, Plasterboard- 12.5mm | 0.26 |

Where studies utilised within the generalised dataset listed construction materials, these listed materials were compared with the UK recommended materials in order to assess suitability, provided location of the case study was appropriate.

#### 3.4.2.3 HVAC systems

The facility was controlled by electrical heating and cooling by means of air conditioning. No natural ventilation was utilised as a cooling mechanism in the facility. HVAC systems were set to fully operational during manufacturing working hours, as well as two hours before this period and one hour after, and set to reduced operation outside of these times.

HVAC set points to ensure thermal comfort conditions were set in accordance to formal recommendation for environmental conditions by ASHRAE [171], with systems adjusting accordingly if conditions were out of the specified range (Table 7).

Table 7- HVAC Set Points

| | **Set Point Range** |
|---|---|
| **Temperature** | 19-22 °C |
| **Relative Humidity** | 30-60% |

The CIBSE guide sets a minimum requirement of 0.5 $l\ s^{-1}\ m^{-2}$ of fresh air supply [167], the recommended rate of 0.8 $l\ s^{-1}\ m^{-2}$ was utilised in this study.

#### 3.4.2.4 Weather Data and Site Location

The ApLocate module in IES-VE provided data regarding latitude, longitude and height above sea level as well as data regarding daylight saving for the chosen location, suburban London. The air surrounding the facility was parameterised with an air density of 1.2 kg $m^{-3}$ and a global current daily average $CO_2$ concentration of 400ppm.

Weather data is provided by the MET Office, and provides data at hourly intervals over the course of a year including dry-bulb temperature, wet-bulb temperature, dew point temperature, direct beam solar radiation, diffuse solar radiation, solar altitude, solar azimuth, wind speed, wind direction, atmospheric pressure, relative humidity and cloud cover for use in thermal calculations.

## 3.5 Development of HVAC Control Systems

Manufacturing production can be split into categories based upon factors such as manufacturing technique, available resources and volume. The categories are as follows [172]:

1. Special project manufacture, where each project is significantly different from the previous, and is therefore a flexible process. Eg, custom buildings, bridges, roads or space shuttles.
2. Manufacture to order, where job orders are not necessarily repeated at regular intervals, making application of complete production planning and control procedures difficult. Eg repair works, jobbing foundries.
3. Manufacture for stock with variation in assembly or between processes, eg car and watch manufacture. Products are made ‘as standard’ for customers in anticipation of demand.
4. Manufacture for stock with little or no variation in the processes for the component manufacture, but not for the assembly and finishing operations. Eg clothing and shoe production.
5. Mass production, where a completed product at one operation is automatically passed on to the next, adopting a standardised process of creating parts in large quantities for a low price.
6. Continuous Production, where parts are processed without interruption, 24 hours a day 7 days a week. Holdups in the system could result in production loss but could also result in adverse effects to a whole batch, of which would have to be rejected.
7. Intermittent production, covering all non-continuous production and covers production such as single project, jobbing or made to order. Most products are

produced in smaller quantities than continuous, with flexible systems to suit production varieties.

Due to the difficulty of production planning and control procedures associated with the manufacture to order technique, a form of intermittent production, this method was selected for analysis in this study, along with the contrasting technique of a more continuous based method, such as manufacture for stock.

The distinct differences between the made to order (MTO) and made to stock (MTS) approach is the type of production, with MTO being an intermittent process with varying machine schedules and work flows throughout the day, whereas MTS is generally production on a more continuous basis.

The methods discussed in this study were applied to both a MTO and MTS based facility, in order to determine the effectiveness of the approaches for contrasting production schedule environments.

Machining in manufacturing is less energy intensive than industries such as food, paper and fuel, with energy consumption linked directly to production schedules and technological trends [173]. Therefore, it is predicted that this sector will possess a relatively flat energy consumption trend. However with a growing population and rising customer demand, adopting energy efficiency strategies is essential to ensure the energy consumption profile of this industry does not see an upward trend, and therefore the HVAC system holds great potential for reduction of energy consumption in this sector, as well as increased energy efficiency in anticipation of an increase in machining output.

All occupied buildings have thermal comfort based requirements, however in contrast to a commercial or residential build, these requirements are harder to maintain in manufacturing environments due to thermal energy flows associated with manufacturing equipment. This study questions the suitability of a traditional thermostat based approach to control of a manufacturing HVAC system, and proposes a HVAC system controlled by both occupant thermal comfort requirements and manufacturing schedules.

### 3.5.1 Thermal Comfort Based HVAC Control

The manufacturing model was set to operate with the traditional and 'standard' procedure in the investigation of the thermal comfort controlled (TCC) system for both the MTO and MTS facilities. The HVAC system was set to operate based on thermal comfort thresholds with a reactive approach, where the system acts to combat any undesirable changes to the environment as and when they happen. The HVAC systems were set to fully operational during the working day as well as hours surrounding working hours, with reduced operation overnight as detailed in section 3.4.1. The simulation was run over the course of 12 months, with machines operating 5 days a week, excluding UK bank and public holidays. Total building energy consumption, HVAC consumption and indoor temperature and humidity of the manufacturing workshop were the main parameters for analysis, analysed for comparison with the manufacturing schedule based HVAC system discussed in section 3.5.2.

### 3.5.2 Manufacturing Schedule based HVAC Control

In order to implement a manufacturing schedule controlled (MFC) HVAC system, a year's worth of energy consumption data, machining waste heat and weather simulation data was exported from the simulation run in section 3.5.1. Data from each month was manually analysed on an hourly basis, with energy consumption analysed alongside machine waste heat and outdoor temperature. Based upon observation, optimum HVAC set points and control profiles were manually determined based upon machine waste heat, and therefore machining schedule, and outdoor conditions. Determined HVAC system control profiles were imported back into IES-VE to determine performance of the environment based upon new HVAC operation schedules. Following each simulation run, results were analysed in terms of building energy consumption, HVAC system consumption and temperature and relative humidity levels to ensure thermal comfort. The methodology was repeated until the developed manufacturing based optimum HVAC schedules provided sufficient thermal conditions. This was performed for both the MTS and MTO based facility, which is further detailed in the preceding section.

### 3.5.3 MTS Based Manufacturing HVAC Control

The MTS based manufacturing schedule was based on data from the facilities utilised to produce the general case study model (section 3.4). The facility was set to operate 5 days a week, with machining commencing at 9am, with a worker break in the morning and afternoon, along with a lunch break. Machining was completed at 5pm (Figure 39).

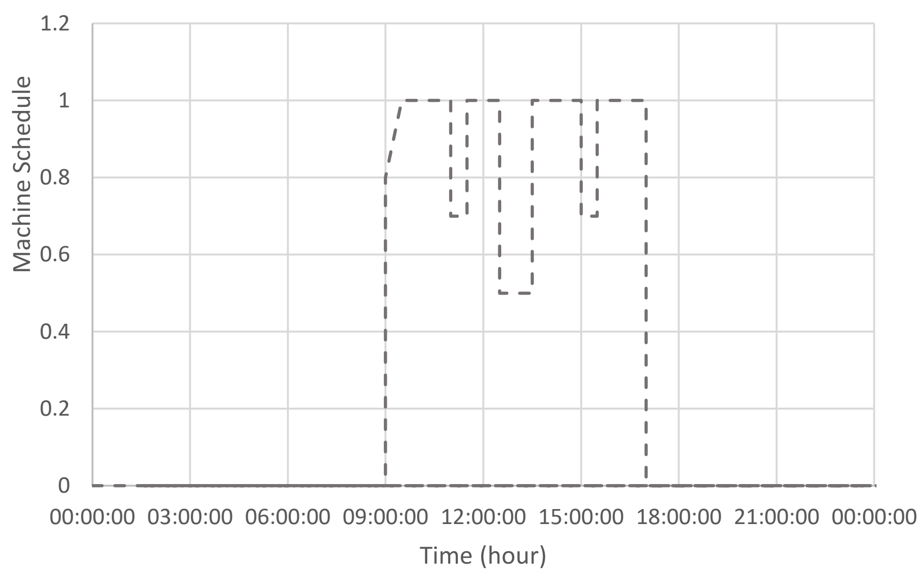



Figure 39- Machine schedule for MTS facility, where an utilisation of 1.0 corresponds to 100% utilisation

For the TCC system, HVAC control was set to fully operational 7am-6pm based on thermal comfort. However for the MFC system, HVAC schedules were based upon manufacturing demand and outdoor conditions, with an example of a developed HVAC schedule seen in Figure 40.

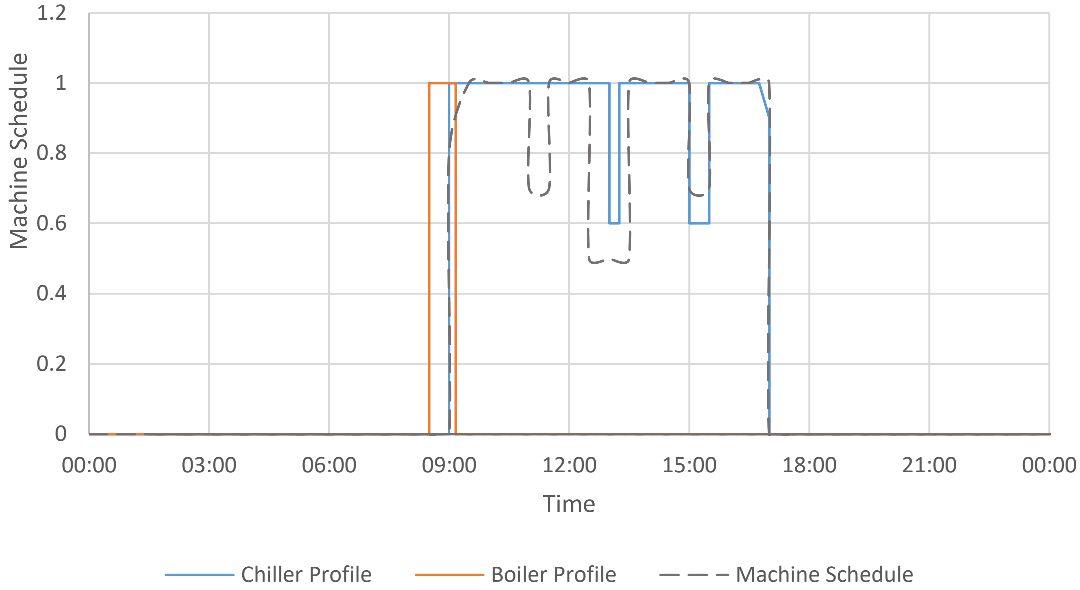



Figure 40- HVAC profile with machine schedule for a day in February, where an utilisation of 1.0 corresponds to 100% utilisation

Further details regarding HVAC schedules for months other than February are detailed in Appendix C.

Boiler systems were turned on at 8:30, prior to worker arrival to ensure comfortable working conditions were satisfied. The boiler systems however were turned off when machining begun, in order to utilise machining waste heat to provide required space heating rather than utilise boiler systems. Chiller systems were modified alongside machine schedule, and were turned down during the lunch hour, when machining was reduced. Boiler systems were not utilised in the months June, July, August and September.

Thresholds for temperature and relative humidity were set as stated in section 3.4.2.3 throughout the optimisation process to ensure thermal comfort requirements were met.

### 3.5.4 MTO Based Manufacturing HVAC Control

In order to model a facility with a realistic MTO machining schedule, schedule data was obtained for an average working week from a MTO based facility in South Yorkshire, UK. This data was used to build up a yearlong manufacturing schedule for use in the MTO facility simulation. Again, the facility was set to operate machinery 5 days a week, utilising boundary conditions specified in Table 1, however in comparison to the MTS based approach, the facility operated between 8am-4pm, as opposed to 9am-5pm, due to operational schedules adopted from the MTO facility in South Yorkshire. An example of schedule for one working day is displayed in Figure 41.

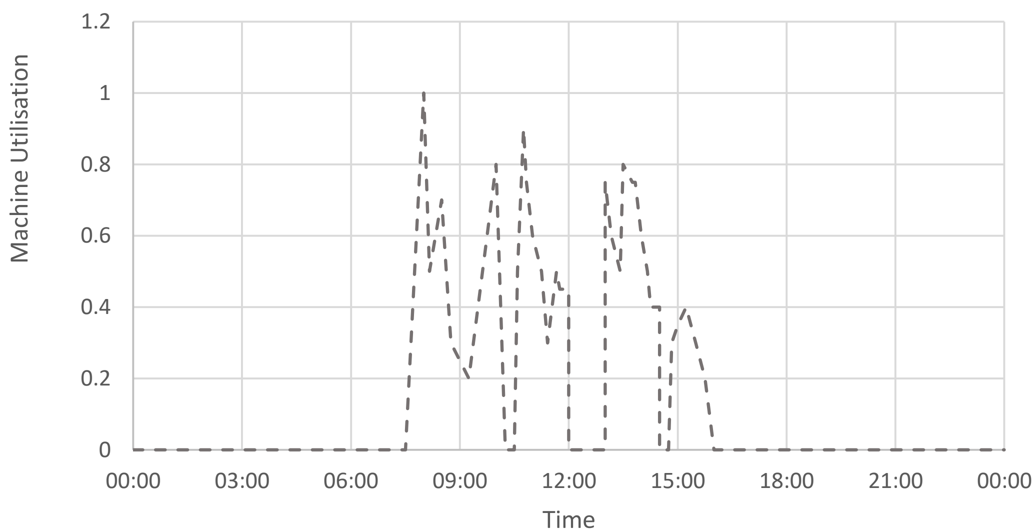



Figure 41- Machine Schedule for MTO facility, where a utilisation of 1.0 corresponds to 100% utilisation

For the TCC system, HVAC control was set to fully operational from 6am-5pm based on thermal comfort. However for the MFC system, an example of a developed HVAC schedule for a typical working day is seen in Figure 42.

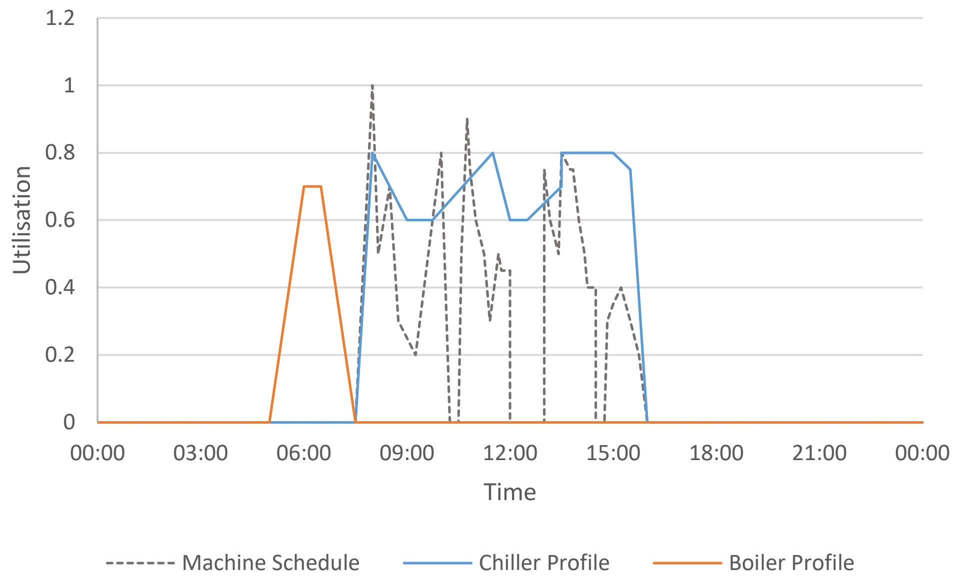



Figure 42- HVAC profile with machine schedule for a day in February where a utilisation of 1.0 corresponds to 100% utilisation

Further details regarding schedules for months other than February are detailed in Appendix C.

Boiler systems were turned on gradually prior to worker arrival to ensure optimum working conditions were satisfied, and turned off before machining begun in anticipation of machine heat gains, providing space heating. Due to the high manufacturing demand at the start of the day, chiller systems were set to compensate for heat gains to the space at 80% operational capacity. The chiller systems operational capacity was then reduced to 60%, due to a reduction in machining. A machining spike was seen at both 10:00 and 10:45, and the chiller profile was set to match this demand, with chiller systems increasing slowly from 9:45 to 11:30.

This was followed by a reduction in machining demand until the afternoon, where a 4th machining spike was seen at 13:00, thus an increase in chiller operational demand was seen, in comparison to the reduction over the lunch period. The operational profile for the chiller system between 12:30 and 13:00 possessed a steeper profile, than that seen in the morning, due to residual heat within the space from a morning of machining. Such an operational profile was found to consume less energy than maintaining high chiller operation over the lunch period, as well as a higher level of thermal comfort.

Chiller systems were kept to 80% operational capacity into the mid-afternoon, and gradually reduced towards the end of the working day. Although the workshop was still in operation when chiller systems were being turned down, the anticipation of the end of the working day and thus reduced heat gains to the space meant that chiller systems could be turned down without compensating for any loss in thermal comfort. Any heat present in the space towards the end of the day did not need to be removed, provided thermal comfort was met whilst occupied, as workers were soon to leave and no additional heat was to enter the space.

Thresholds for temperature and relative humidity were set as stated in section 3.4.2.3 throughout the optimisation process to ensure thermal comfort requirements were met.

## 3.6 Summary

The key difference between the well researched method of DES for analysis of manufacturing environments and the continuous based simulation paradigm used in this thesis is the ability to build up a full continuous energy profile of the manufacturing environment at defined time steps, as opposed to state based analysis with computations conducted at the time of an event/ state change. The use of the time based simulation tool IES-VE, allows this continuous computation and analysis, alongside modelling of manufacturing schedules, weather effects, occupants and building fabrics for a full holistic analysis. Such simulation modelling further allows for a complete dataset to be generated for subsequent analysis by predictive algorithms, allowing for the development and implementation of an intelligent HVAC control system.

The case study utilised in this study, developed from peer reviewed journal papers, provides a pre-validated dataset and manages uncertainties associated with data collection from sensor systems. The case study environment was modelled adopting two contrasting production schedules, the stochastic 'Made to Order' and more continuous 'Made to Stock' regime, to determine the effectiveness of the intelligent HVAC control approach to different manufacturing environments.

# Chapter 4- Machine Learning Techniques for a Proactive HVAC system

## 4.1 Introduction

This chapter introduces a number of techniques for the prediction of building and HVAC energy consumption as well as indoor conditions utilising the manufacturing controlled HVAC approach.

Predictive analytic models and techniques are used to determine patterns in data and to predict outcomes based on these patterns. The technique used is dependent upon size of input and output variables, the relationship between variables, data type and required output. Amongst the most basic of techniques used for predictive energy analysis is linear regression, and with increasing complexity, decision trees, random forest, neural networks and deep neural networks.

Section 4.2 discusses the coupling of simulation and machine learning models. Section 4.3 discusses model validation, with predictive models introduced in sections 4.4, 4.5, 4.6 and 4.7. Section 4.8 utilises the predictions of building energy demand to identify spikes in energy consumption, with simulation utilised to optimise schedules for a reduction in peak energy demand. The chapter is concluded in section 4.9 where a machine learning model is utilised to predict optimum HVAC set points, of which were used to run a simulation model utilising a proactive HVAC control approach.

## 4.2 Training from simulation

Utilising data from simulation for predictive analysis allows for extensive analysis in a low cost, risk free manner without the need for sensor implementation, and also allows for the development and testing of predictive control methodologies, for example, this method has been utilised in the development of driverless cars. In this study, simulation data from investigations discussed in section 3.5.2 is utilised to train a number of predictive algorithms.

The simulation models of the MFC environment for both the MTS and MTO environments are utilised to train linear regression, ANN, DNN and random forest models for the prediction of building and HVAC energy, indoor air temperature and humidity.

In the development of such predictive models, data was manually exported from IES-VE into the subsequent algorithm. The computational language of Python was used for algorithm development, along with libraries such as NumPy [174] and Pandas [175] for data manipulation, Matplotlib for data visualisation [176], and Scikit-Learn, [177], and Keras on Tensorflow, [178], for development of statistical and machine learning models.

The outputs from simulation, and thus the inputs and outputs to all predictive models is displayed in Table 8.

Table 8- Predictive model inputs and outputs

| Inputs | Outputs |
|---|---|
| Occupancy internal gains (kW) | Total building energy consumption (kW) |
| Outdoor temperature (° C) | HVAC energy consumption (kW) |
| Outdoor relative humidity (%) | Workshop air temperature (° C) |
| Outdoor wind speed (m $s^{-1}$) | Workshop relative humidity (%) |
| Cloud Cover (oktas) | |
| Manufacturing demand (kW) | |

For all predictive models, data at one-hour intervals across a 12-month period was utilised.

## 4.3 Validation

For the computational assessment of a whole building, compliance with ASHRAE regulations provides the following requirements [157]:

- Model 8760 hours per year
- Include thermal mass effects
- Occupancy and operating schedules that can be separately defined for each day of the week and holidays,
- Individual set-points for thermal zones or HVAC components,
- Actual weather data
- User-definable part-load performance curves for mechanical equipment, and user-definable capacity and efficiency correction curves for mechanical equipment operating at non-rated conditions

All ASHRAE guidelines were followed, with the exception of the use of efficiency correction curves for mechanical equipment, as efficiency corrections were defined for each piece of placed equipment. For example, specification of lighting, computer and machining schedules, occupancy based lighting switches and power saving specifications for computational equipment.

The performance of predictive models can be determined using accuracy metrics. Common metrics include mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), coefficient of variation of the root mean square error (CV(RMSE)) and coefficient of determination ($R^2$). A review of energy planning models stated that the most commonly utilised metric was RMSE, MAE and MAPE [112].

Studies commonly use a combination of metrics in analysis of a model due to disadvantages and limitations to each metric. For example RMSE and MAE are scale dependant, whereas MAPE is scale independent [179]. RMSE and MAE are thus not recommended for comparison between different models and studies. MAPE however is undefined if Y is zero at any point in time [180], and is not a documented metric in the Scikit-Learn library due to such limitations.

This studied utilised the CV(RMSE) and $R^2$ metric, due to recommendations and stated accuracy criteria and recommendations in the ASHRAE guidelines [157] (Table 9).

Table 9- Calibration criteria and model recommendations set by the ASHRAE guidelines

| **Metric** | | **Calibration Criteria** |
|---|---|---|
| **CV(RMSE)** | Monthly criteria (%) | 15 |
| | Hourly criteria (%) | 30 |
| | | **Model recommendation** |
| **$R^2$** | | > 0.75 |

In this study, CV(RMSE) and $R^2$ was calculated on an hourly basis at each simulated time step. The metrics were then averaged over all data points.

CV(RMSE) (%) measures the variability of the errors between measured and simulated values, giving an indication of how well the model can predict the overall pattern of the data [181]. It is calculated by normalising the RMSE metric by the dependant variable (Equation 16).

$$CV(RMSE) = \frac{1}{\bar{y}_{observed}} \sqrt{\frac{\sum_{i=1}^{n}(y_{observed,i} - y_{forecast,i})^2}{n}} * 100$$

Equation 16- CV(RMSE) metric ([182])

Where n is equal to the number of measured data points, $y_{observed,i}$ are the measured/ observed variables, $y_{forecast,i}$ the predicted variables and $\bar{y}_{observed}$ the mean of the measured/ observed variables.

CV(RMSE) quantifies average error rather than the error over individual data points and therefore provides a good metric for overall model performance.

$R^2$ measures how well the model is likely to perform with new data, and ranges between minus one and plus one (Equation 17). The best possible score is one, with a score of zero implying that the model predicts the target value whilst disregarding any input data, and a negative value implying the model cannot perform predictions on new data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{observed,i} - y_{forecast,i})^2}{\sum_{i=1}^{n}(y_{observed,i} - \bar{y}_{observed,})^2}$$

Equation 17- $R^2$ metric ([183])

CV(RMSE) and $R^2$ were used in the model development stage, comparing each individual model through hyper-parameter optimisation. $R^2$ and the errors obtained on unseen data predictions were used to compare different models.

The predictive models were also used to predict outputs in Table 8 using an unseen dataset consisting of one months' worth of data in order to determine the accuracy of the model for further use. The use of unseen data confirms whether the model has successfully learnt patterns in the data, rather than learning specific inputs and its corresponding output variables.

## 4.4 Linear Regression

Beginning with one of the simplest predictive approaches, ordinary least squares multiple linear regression (LSMLR) was first utilised for prediction of building and HVAC energy demand as well as indoor temperature and humidity. This technique was utilised due to its simplicity and long-standing ability to recognise patterns in data.

Linear Regression is used to determine the relationship between two continuous variables (Equation 18), finding a linear relationship between the input, x, and output y, returning a line that results in the least error.

$$y = \beta_o + \beta_1 x$$

Equation 18- Linear Regression ([184])

Where y is the response variable, $\beta_0$ the intercept of the relationship, $\beta_1$ the regression coefficient and x the input variable.

Multiple linear regression is the approach taken when there is more than one input variable (Equation 19).

$$y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_n x_n$$

Equation 19- Multiple Linear Regression ([184])

Where n is the number of input variables.

Least squares is the most common method for fitting a line of best fit of data by minimising the sum of the squares of the vertical deviations from each data point to the line. The method treats the data like a matrix and uses linear algebra to estimate optimal values for the coefficients.

Linear regression models are advantageous in that they do not require a large amount of input data and provide a simplistic model requiring minimal computational cost.

A LSMLR model was built for both the MTO and MTS environments.

## 4.5 Artificial Neural Networks

ANNs are a popular tool for energy demand forecasting and energy planning management due to their ability to approximate nonlinear processes to a high degree of accuracy. This model was selected for such reasons, along with the model's capability to recognise complex patterns in data with multiple inputs and outputs. The model also allows for extensive modifications, such as addition of layers in order to determine specific features from the data. A feed forward ANN was utilised, in which information flows through the model, from the input, through intermediate computations towards the output, with no loops or feedback connections.

ANNs are based upon the structure of the human brain, utilising nodes or neurons in layers connected by pathways or synapses (Figure 43).

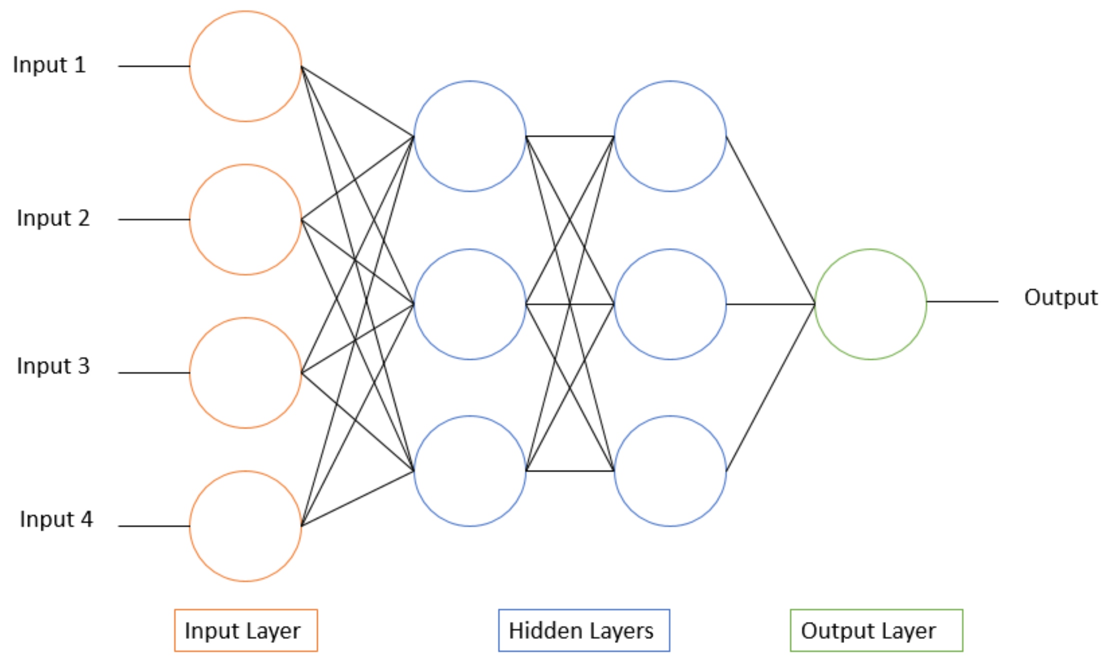



Figure 43- Artificial Neural Network Architecture

The number of neurons in the input layer corresponds to the number of predictors (number of model inputs) whereas the number of neurons in the output layer correspond to the number of target or output variables. The hidden layers in the model are used to recognise patterns and features, with models with more than one layer being considered Deep Neural Networks. The optimum number of layers is determined by number of inputs, outputs and sample size, but is commonly determined by trial and error or an iterative approach due to the complexity between number of layers and size of datasets.

Neurons in the model are connected by synapses which hold a weight linked to the relationship between neurons, which is altered during the training process. A cost function quantifies the error of predictions made by the model during the training process and is thus used to improve the accuracy of the model. The gradient descent algorithm is used to alter the weights to values which make the cost function a minimum. The most common gradient descent algorithm is the Back-propagation algorithm, a computationally efficient method used for models in which the outputs are known (supervised neural networks).

The relationship between the input and output of the network is determined by the activation function, which performs a nonlinear transformation to the input making it able to learn and perform complex tasks. Without such a function, the model presents a linear regression approach. Common activation functions include the Rectified Linear Unit Function (ReLu), Sigmoid and Hyperbolic Tangent (tanh), with suitability of each function dependent upon the models purpose and location of the layer.

There is no standardised method to determine the optimum number of neurons in the hidden layer, however Panchal et al. [185] discuss a number of approaches such as:

- The number of hidden neurons should be in the range between the size of the input and output layers.
- The number of hidden neurons should be 2/3 of the input layer size plus the size of the output layer.
- The number of hidden neurons should be less than twice the input layer size.
- The number of hidden neurons is determined with a trial and error approach, starting from 2 neurons.
- The number of hidden neurons is determined with a configuration of l-m-n, where l is the input nodes and n is the output, eg if there are 2 input and output nodes, the number of hidden nodes is 2.

Due to the great amount of uncertainty in the optimum number of hidden neurons, a trial and error approach was taken, increasing the number of neurons by 1 after analysis of $R^2$ and CV(RMSE) metrics, as well as the error of predictions made on unseen data (Table 10).

The ANN model was built with the inputs and outputs listed in Table 8, for the MTS and MTO approach.

Table 10- Results for the iterative approach to determining optimum number of neurons in the hidden layer

| Model | Number of Neurons in Hidden Layer | R2 | CV(RMSE) (%) |
|---|---|---|---|
| **MTO** | 2 | 0.62 | 65.12 |
| | 3 | 0.83 | 45.4 |
| | 4 | 0.88 | 39.5 |
| | 5 | 0.90 | 34.5 |
| | 6 | 0.87 | 39.5 |

| Model | Number of Neurons in Hidden Layer | R2 | CV(RMSE) (%) |
|---|---|---|---|
| **MTS** | 2 | 0.69 | 42.1 |
| | 3 | 0.89 | 27.8 |
| | 4 | 0.93 | 22.2 |
| | 5 | 0.93 | 22.0 |
| | 6 | 0.93 | 22.8 |

The final model had 5 neurons in the hidden layer. This also follows one of the 'rules of thumb' for neural network design, such that the number of inputs follows $\frac{no.of\ inputs+no.of\ outputs}{2}$; a methodology also adopted by Fan et al. for the use of neural networks for building cooling load prediction [179].

A one-layered ANN was built in this study, consisting of 6 inputs, 4 outputs and one hidden layer. The hidden layer consisted of five neurons (Figure 44).

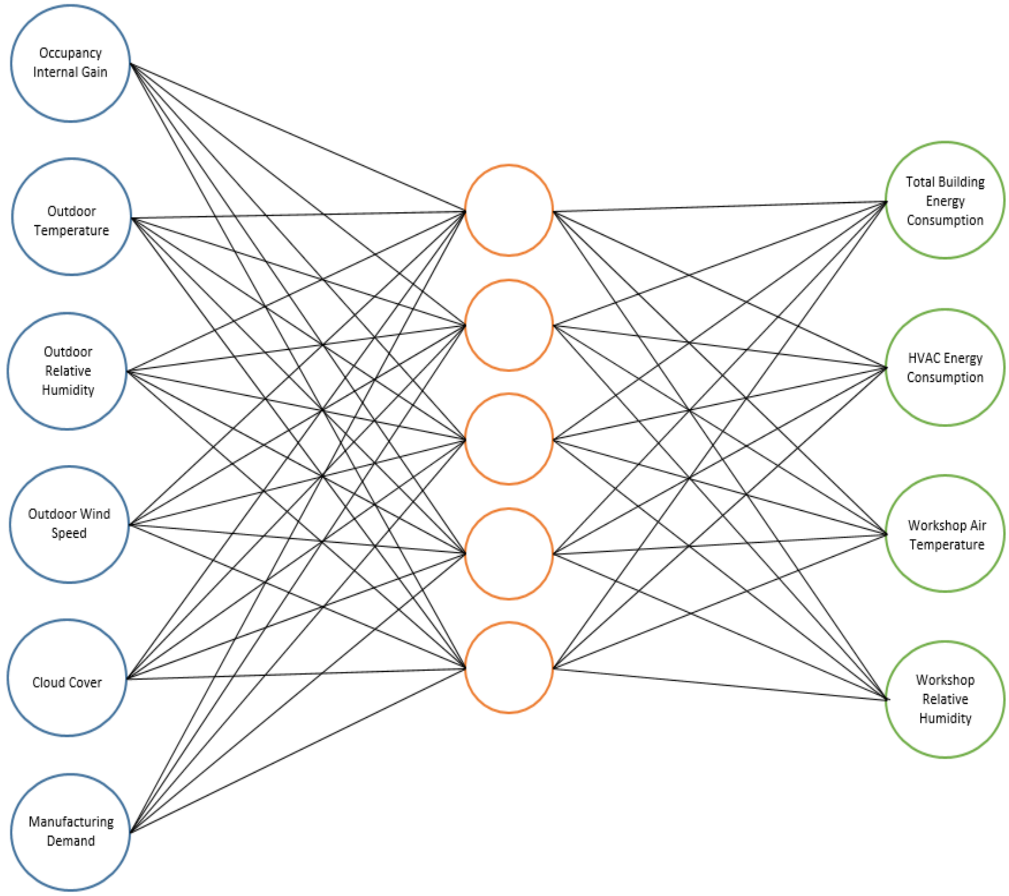



Figure 44- ANN architecture for prediction of building and HVAC energy, and indoor conditions

### 4.5.1 Data Pre-processing

Prior to model training, data splitting is required to create training, validation and testing datasets. The training dataset is the data from which the model learns and from which it is trained, the validation set is used to evaluate the model that is fitted on the training dataset whilst tuning model hyper-parameters (e.g. learning rate, number of iterations, activation function), whereas the test dataset is used to provide an evaluation of the final model, and is used once the model is completely trained using training and validation sets [186] (Figure 45).

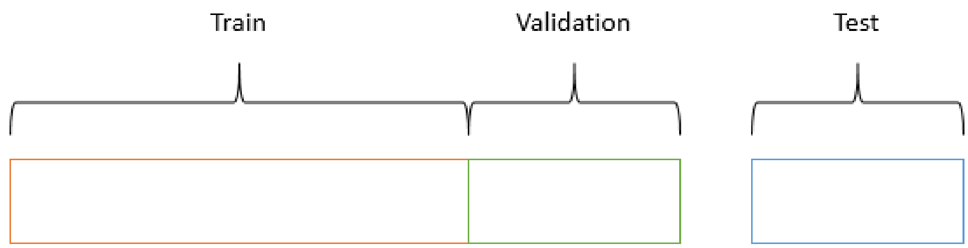



Figure 45- Data train, validation, test split (reproduced from [186])

In order to build this split, a number of methods can be utilised, commonly test-train-split or K-fold cross validation.

Test-train-split is a simplistic method in which data is split into groups based on percentages of data, of which is commonly a 80:20 train test split [187] (Figure 46). However such a methodology has been criticised, with the potential to lead to overfitting because depending upon how data is split, there may not be an accurate representation of all variables in the training set.

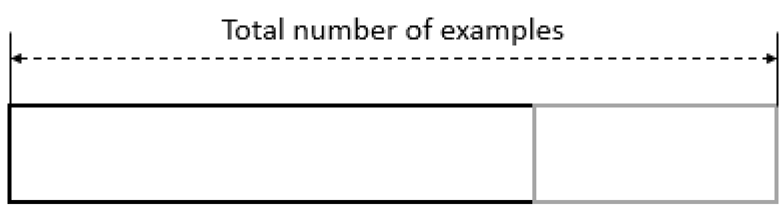



Figure 46- Test-train-split modelling methodology (reproduced from [186])

Therefore k-fold cross validation is commonly used in order to avoid bias caused by the randomness in choosing testing and training sets in the test-train-split method [188]. Data is shuffled and split into k folds/groups, where one group is used as a validation set and the remainder used to train the model. This process is repeated until every fold has been used as the test set (Figure 47).

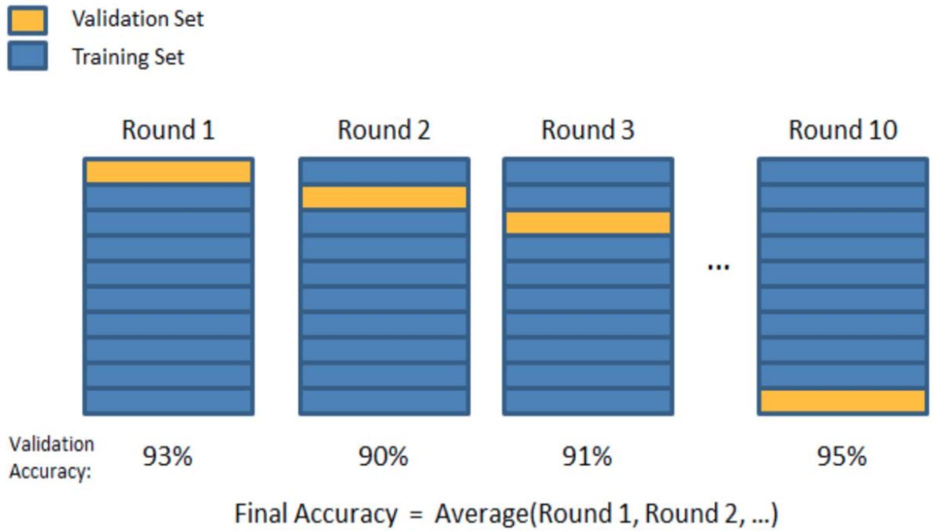



Figure 47- K Fold cross validation methodology (reproduced from [186])

Due to the use of small weights, data scaling and standardisation of input and target variables is required in order to ensure model convergence and accurate predictions, as well as reducing the risk of exploding gradients and a slow learning process [189]. The aim is to ensure features represent normally distributed data.

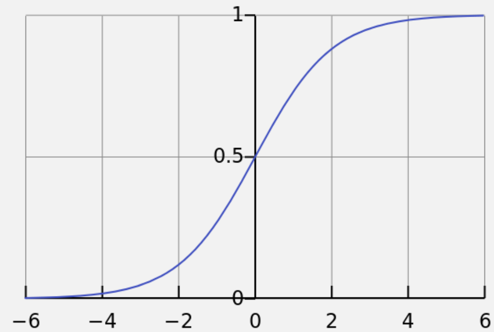
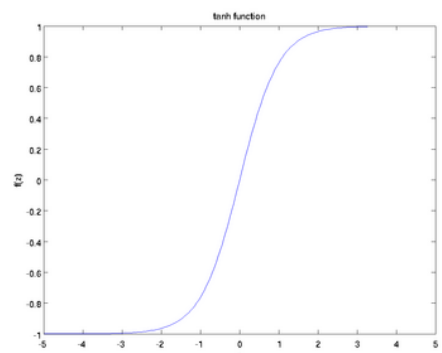
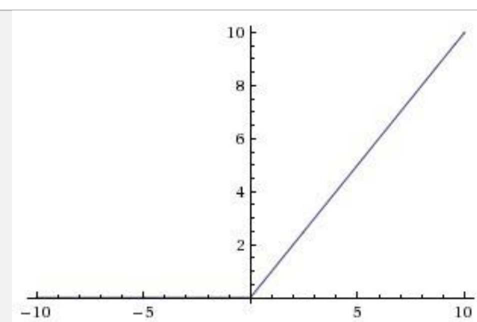
Data in this study was scaled so that all values were within the range of zero to one, utilising Scikit-Learns MinMaxScaler (Equation 20).

$$x_{norm}^{(i)} = \frac{x^{(i)} - x_{min}}{x_{max} - x_{min}}$$

Equation 20- MinMax scaling ([184])

The activation function performs a nonlinear transformation to the input making it able to learn and perform complex tasks. The activation function is applied to the sum of the inputs and their corresponding weights in order to obtain the output of that layer. The function keeps values moving forward to subsequent layers of the network and towards the output, as well as maintaining values within an acceptable range. Popular types of activation function are displayed in Table 11.

Table 11- Popular activation functions ([190])

| Type | Equation | Range | Graph |
|---|---|---|---|
| logistic | $f(x) = \frac{1}{(1 + \exp(-x)}$ | 0 - 1 |  |
| tanh | $f(x) = \frac{2}{(1 + \exp(-2x)} - 1$ | -1 – 1 |  |
| ReLu | $f(x) = \max(0, x)$ | 0 - inf |  |

Logistic functions are well suited to classification models, and are prone to vanishing gradients resulting in slow or no learning. Tanh is a scaled form of the logistic function, with stronger gradients, however still suffers a vanishing gradient problem. The ReLu function is less computationally expensive as not all neurons are activated at the same time. However ReLu can have a 'dying ReLu' problem where the gradient of the activation function nears zero. In order to determine the best function for this study, all functions were tested. Due to similar $R^2$ and CV(RMSE) scores (Table 12), each model was used to predict on new unseen data with errors compared. The tanh activation function was utilised for both the MTO and MTS models. Although $R^2$ and CV(RMSE) metrics were similar for all activation functions, the tanh function showed a significant improvement in accuracy for the MTS approach when the model was used to make predictions on unseen data (Table 13). For the MTO model, all functions performed with similar accuracy, with the tanh approach obtaining a slightly lower CV(RMSE).

Table 12- Activation function investigation for the MTO and MTS models, accuracy metrics

| **Model** | **Logistic** | | **Tanh** | | **ReLu** | |
|---|---|---|---|---|---|---|
| | R2 | CV(RMSE) (%) | R2 | CV(RMSE) (%) | R2 | CV(RMSE) (%) |
| **MTO** | 0.90 | 34.5 | 0.90 | 28.1 | 0.90 | 34.5 |
| **MTS** | 0.93 | 22.1 | 0.93 | 17.4 | 0.93 | 21.98 |

Table 13- Activation function investigation for the MTO and MTS models, predictions on new data

| Model | Output Parameter | Activation Function, Error (%) | | |
|---|---|---|---|---|
| | | Logistic | Tanh | Relu |
| MTO | Building Energy | 12.1 | 12.8 | 12.5 |
| | HVAC Energy | 11.0 | 11.2 | 11.4 |
| | Temperature | 4.68 | 4.63 | 4.75 |
| | Humidity | 6.42 | 6.06 | 6.73 |
| MTS | Building Energy | 17.3 | 11.0 | 14.2 |
| | HVAC Energy | 16.7 | 12.4 | 12.7 |
| | Temperature | 4.43 | 4.27 | 4.58 |
| | Humidity | 6.34 | 6.38 | 6.82 |

The optimisation algorithm is used to change the weights of neurons so that the next evaluation is made with a lower error, and therefore the optimisation seeks to navigate down a gradient of error.

Although the most common optimiser is the stochastic gradient descent (SGD), the Adam optimiser is increasingly being used to involve accuracy scores and is the default optimiser offered by Scikit-Learn. Furthermore, adding momentum to the model can be used to accelerate gradient descent smoothing out oscillations and accelerating gradient decent where the gradient remains relatively consistent across training steps, taking into account previous gradients with each iteration. The use of the Nadam optimiser is a form of the Adam optimiser in which Nesterov momentum is applied prior to error gradient computation, and has shown significant improvements over the use of the Adam optimiser. The use of Nesterov momentum can be thought of as an improved momentum, as it ensures that the gradient and momentum are facing the correct direction for gradient descent, reducing gradient overshoot problems. The Nadam optimiser was used for all neural networks in this study.

## 4.6 Deep Neural Networks

Mawson and Hughes [191], demonstrate the potential for the use of feed forward and recurrent deep neural networks for the prediction of energy consumption and indoor conditions within the manufacturing sector. The work was expanded on in this study, through the adoption of DNNs for prediction of building energy consumption, HVAC energy and indoor air temperature and relative humidity for the generalised case study discussed in section 3.5.2.

The DNN model was used with the inputs and outputs listed in Table 8, for the MTS and MTO approach.

The DNN consisted of a similar architecture to that displayed in Figure 44, with an additional hidden layer (Figure 48). The number of neurons in each layer of the DNN was again determined with an iterative approach. Where j is equal to the number of neurons in the first hidden layer, and k the number of neurons in the second hidden layer, $R^2$ and CV(RMSE) metrics were analysed for a range of 2-6 for j and k to determine the optimum model architecture. Furthermore, $R^2$ and CV(RMSE) metrics were analysed for the use of the ReLu, tanh and logistic activation functions. The metrics obtained for the optimised model are displayed in Table 14. Moreover, the model was used for predictions on unseen data, displayed in Table 15.

Table 14- Optimised DNN Models, where i, j, k, z is the number of neurons in the input layer, the first hidden layer, the second hidden layer and the number of output neurons respectively

| **Model** | **MTO** | **MTS** |
|---|---|---|
| **Number of neurons (i, j, k, z)** | (6,6,6,4) | (6,6,6,4) |
| **Activation function in hidden layer** | tanh | tanh |
| **R2** | 0.89 | 0.92 |
| **CV(RMSE) (%)** | 31.5 | 19.32 |

Table 15- DNN model errors on unseen dataset

| **Model** | **Output parameter** | **Error (%)** |
|---|---|---|
| **MTO** | Building Energy | 33.8 |
| | HVAC system energy | 15.5 |
| | Temperature | 4.83 |
| | Humidity | 6.93 |
| **MTS** | Building Energy | 36.6 |
| | HVAC system energy | 20.9 |
| | Temperature | 4.53 |
| | Humidity | 6.88 |

As used in the ANN in section 4.5, the Nadam optimiser was utilised for all DNN.

The architecture of the DNN is displayed in Figure 48.

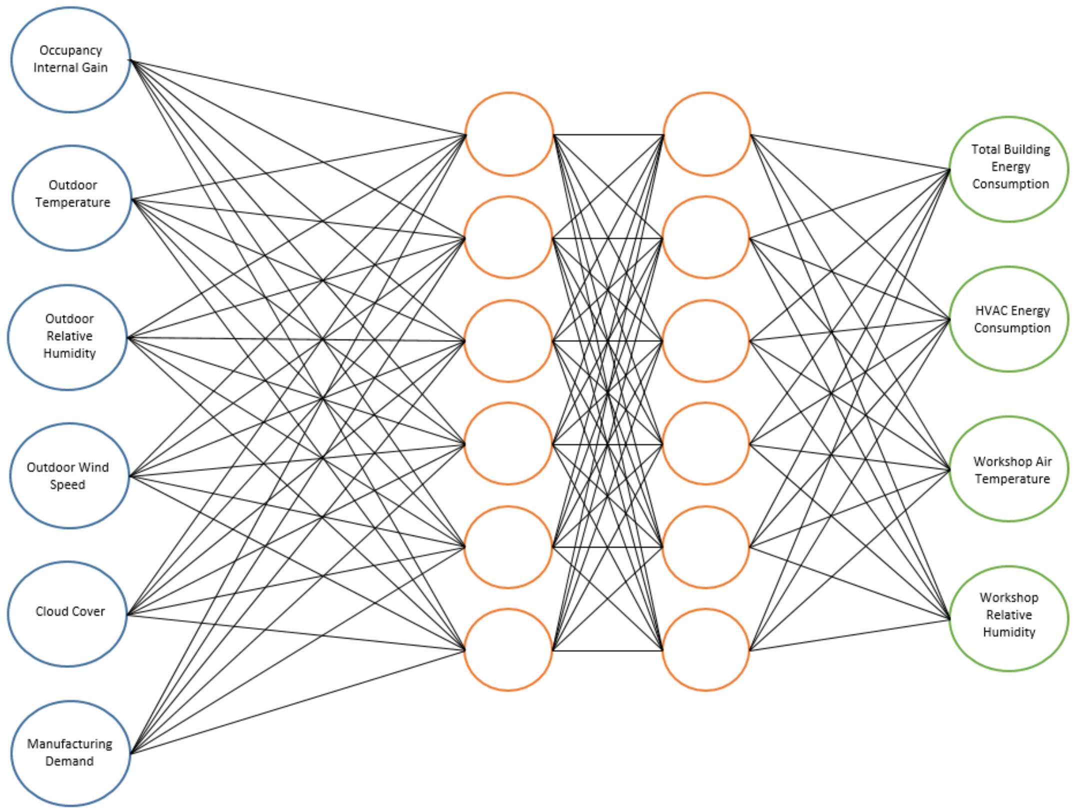



Figure 48- DNN architecture

## 4.7 Random Forest

Although studies have shown the potential of the use of random forests for predictions in the energy sector, the methodology is still relatively novel and not yet prevalent in building energy predictions. Thus the method was selected in order to expand on existing knowledge pertaining to random forests for use in the energy sector.

Random forests consist of many individual decision trees that operate together as an ensemble. A decision tree has a flow chart architecture (Figure 49), where the root node represents a dataset, the decision node is created when this root node is split, and also at the splitting of each subsequent sub node, and the leaf/terminal node represents the decision/ final node. A branch is a sub section of the tree. The splitting process continues until a decision is reached. 'Pruning' is the removal of sub nodes, in order to prevent overfitting. A random forest model splits branches in a way in which reduces the mean squared error of the model.

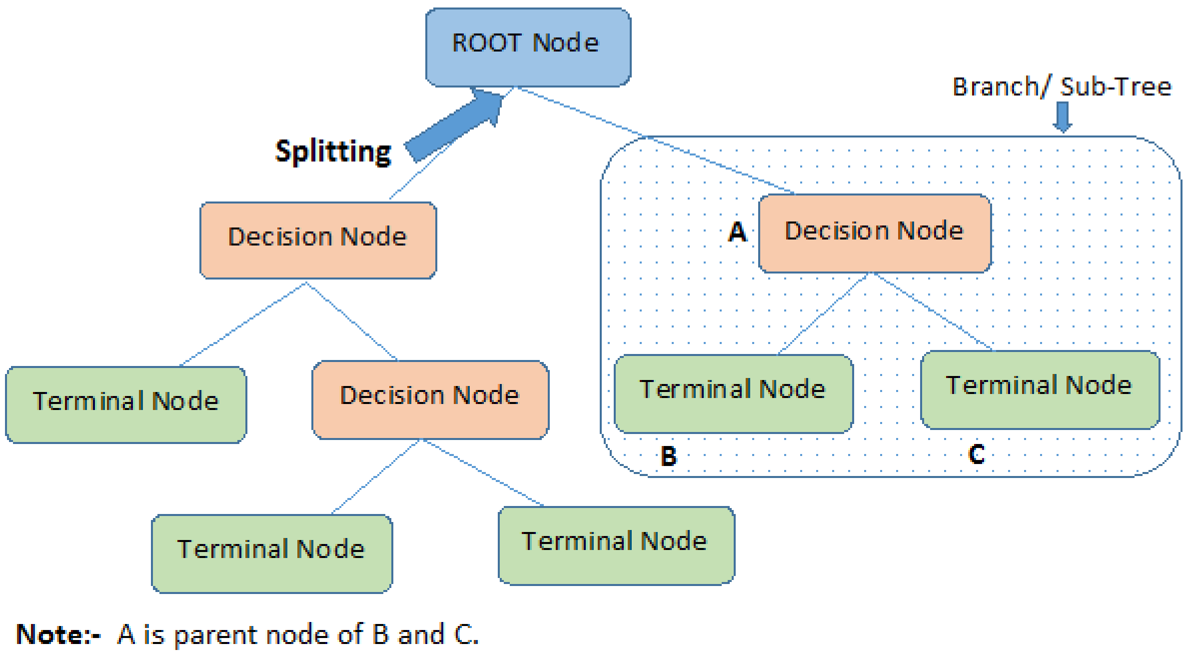



Figure 49- Random Forest model architecture [192]

Such a method provides a higher level of accuracy, as well as more stable predictions, than the use of individual trees, as any errors present in one tree do not impact the errors of others, the trees in the forest run in parallel, and the model gradually achieves the correct result through averaged results of individual trees.

This is done by utilising Bootstrap Aggregation (Bagging) and feature randomness.

Bootstrapping is the process in which individual trees take a sample from the dataset with replacement (some data will be used multiple times in a single tree). Data is not split between individual trees, rather providing all trees with the same size of data as the original dataset. Thus, repeatedly using data from the original training set in order to produce multiple separate training sets (Figure 50).

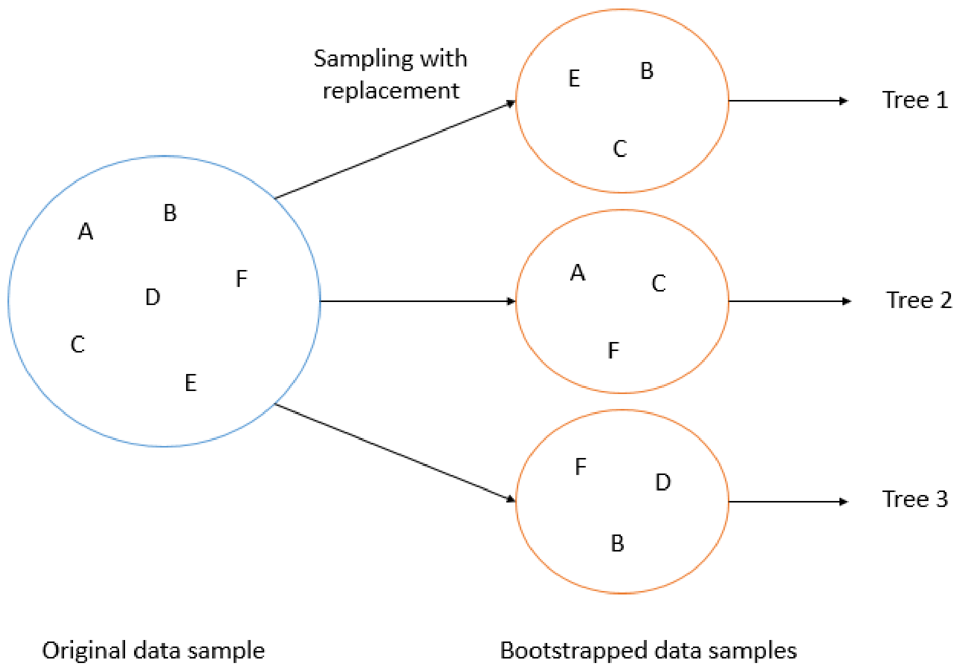



Figure 50- Data sampling procedure for random forests

Bagging is the process of combining predictions from many individual models or algorithms to make a more accurate prediction than a single model.

Features are used to split nodes, and using the process of feature randomness, instead of searching for the most important features when splitting a node, it searches for features amongst a random set. Therefore, each individual tree uses different features to make decisions. Each time a split is made, a random feature is used.

In contrast to neural networks, cross validation or the use of separate test data sets is not required as such similar methodology is applied internally with the use of bootstrapping.

In summary, each tree in the Random Forest is built upon a bootstrapped sample of data. Using this dataset, only a subset of variables is used at each step of growing the tree, with a random feature used at each node split. This process is repeated, using whichever feature gives the best split in order to split nodes iteratively until the trees have grown. With this process repeated for each tree, the resulting forest holds a wide variety of trees- thus random forest. This process provides a single observation for the forest based on the result of the many trees.

A random forest regression predictor can be expressed as in Equation 21.

$$\hat{f}_{RF}^{C}(x) = \frac{1}{C}\sum_{i=1}^{C} T_i\,(x)$$

Equation 21- Random forest regression predictor ([193])

Where x is the vectored input variable, C the number of trees and Ti(x) is a single regression tree constructed from a sample of input variables and bootstrapped samples [138].

Node impurity is used to determine how well trees split the data, and can be thought of as the variance in a node. The error drop can be calculated at each split point for a certain variable. Therefore, it can be used as a method of determining how importance certain features are to the random forest model. This allows certain features to be removed from the dataset if deemed un-important.

The random forest model was built based on the inputs and outputs listed in Table 8, for the MTS and MTO approach.

Similar to the study on building energy prediction undertaken by Fan et al. [179], the random forest optimisation was performed over tree depth, which specified the length of the longest path from a root to a leaf, with a deeper tree having more splits and the potential for more information capture. A tree depth of 3 to 21 was analysed in this study. Furthermore, the number of estimators and maximum features was optimised, where the number of estimators is equal to the number of trees in the forest, where increasing the number of trees increases learning ability however also slows down the learning process. The number of features specifies how many features should be considered when looking for the best model split, with a larger number improving model performance as each tree node is considering a larger number of options, but will reduce processing speed [194].

The number of estimators analysed held values of 10, 100, 500 and 1000, and maximum features ranged from 2-4. The Grid Search method was utilized, evaluating all possible combinations of tree depth, number of estimators and maximum features, thus trialling 272 possible combinations. The parameters utilized in the optimised model are displayed in Table 16.

Table 16- Parameters utilised in the Random Forest model for the MTS and MTO approach

| Model | Tree depth | Estimators | Max features |
|---|---|---|---|
| **MTS** | 19 | 1000 | 4 |
| **MTO** | 19 | 1000 | 4 |

Feature Importance was performed, with Table 17 displaying variables in order of importance.

Table 17- Feature importance, from most important to least

| Importance | |
|---|---|
| | Manufacturing Demand |
| | Occupancy Internal Gains |
| | (External) Dry- Bulb Temperature |
| | Cloud Cover |
| | Humidity |
| | Wind Speed |

Although the manufacturing demand and occupancy levels were determined to be of higher importance than external climatic conditions, with humidity and wind speed having low feature importance, these features remained in the dataset. It was concluded that climatic features were required in order to determine the impact of seasonal variations on building energy demand and HVAC requirements.

## 4.8 Peak demand investigation and spike reduction

A monetary incentive for manufacturing companies is to reduce their peak energy demand in order to avoid associated demand costs.

The predictive algorithm discussed in 4.7 was utilised to predict future building energy demand, and thus identify any potential spikes in energy consumption. Identifying these spikes in consumption before they happen allows for manufacturing and HVAC schedule optimisation in order to reduce and avoid such spikes, and thus avoid the high costs associated with energy spikes.

The MTO facility was chosen over the MTS facility, due to schedule fluctuations, and more flexible scheduling which allowed for optimisation, whereas the more continuous nature of the MTS facility had less potential for change.

Typically, peak demand reduction has been performed by machine schedule optimisation. This study adopted a similar approach, however due to the impact of manufacturing heat gains on HVAC systems, HVAC system control was optimised alongside manufacturing schedules in order to ensure that indoor thermal conditions were satisfied. Furthermore, previous peak reduction studies have focused on cutting costs and have achieved this at the expense of an increase in energy consumption. Therefore in this study, throughout the optimisation process, energy consumption was kept as a constant, or aimed to be reduced where possible.

Machine ramp up is a common cause of spikes in an energy consumption profile due to the sudden turn on of systems at the start of production, and thus was a starting point at levelling the energy profile by adopting a 'soft start' approach to machining. Rather than an immediate facility switch-on when workers arrived, machine start-up was staggered. Alongside the staggered start to machining, HVAC systems were set to a lower setting at the start of the day due to anticipated heat gains from equipment. Machining was also reduced towards the end of the day with a staggered approach. In a real manufacturing environment, it may not be possible to change scheduling of some equipment due to manufacturing demands or operational mature of the machine. Thus, throughout the optimisation process, the amount of machine utilisation throughout the facility was not reduced below 50%, with the exception of staggered starting of machine turn-on, and lunch break operation.

Furthermore, machine worker breaks were altered, with staggered breaks for workers, as well as continuous machining through the lunch hour, in order to avoid a rapid reduction in machining energy consumption and to also help to maintain a more consistent thermal environment, without fluctuating heat gains from machining equipment avoiding the requirement for environmental modification from the HVAC system.

The original manufacturing and HVAC schedule with the corresponding energy consumption for a typical working day in May is displayed in Figure 51.

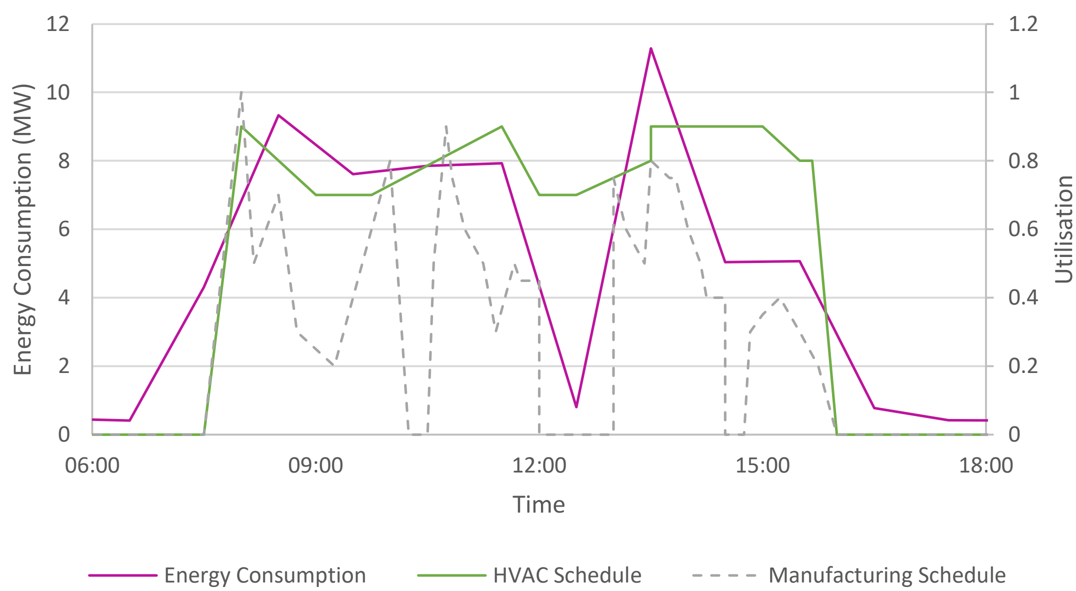



Figure 51- Manufacturing and HVAC schedule along with energy consumption for a manufacturing HVAC controlled MTO environment, where an utilisation of 1.0 corresponds to 100% utilisation

Such a profile was used as the starting point for both HVAC and manufacturing schedule optimisation. Again, temperature and humidity levels within the workshop was monitored to ensure occupant thermal comfort.

## 4.9 Prediction of HVAC Set Points

Section 3.5.2 discussed HVAC control based upon manufacturing demand and requirements as opposed to the traditional reactive thermal comfort-based system. Such simulations were run based upon manual specification of optimum set points based upon manufacturing demand, occupancy levels and outdoor weather conditions. Such a system and manual specification of HVAC set points is time consuming and requires extensive knowledge based upon the interactions between thermal flows within the building, of which required simulation and multiple investigations to determine optimum set points. In order for the proactive manufacturing based HVAC system to be feasible, these optimum set points needed to be determined analytically, and automatically.

Sections 4.4, 4.5, 4.6 and 4.7 investigated the suitability of a number of predictive techniques for the prediction of building and HVAC energy as well as workshop air temperature and indoor humidity. The predictive models were modified to allow for the addition of HVAC set point as an output parameter, based upon manufacturing demand, occupancy levels and outdoor weather conditions, for the development of a proactive manufacturing based HVAC system.

CV(RMSE) determines the closeness of predicted values to actual variables, whereas $R^2$ determines how much of the variability in the measured values has been learnt by the model, with CV(RMSE) utilised to compare individual models through hyper-parameter optimisation, rather than to compare the performance of different predictive techniques. The method that obtained the best performance in terms of $R^2$ and the lowest errors in predictions on new data sets was selected for use in further development towards a proactive HVAC system.

The random forest method for a MTO manufacturing environment significantly outperformed the LSMLR, ANN and DNN model and thus was utilised for development of the proactive HVAC. In terms of the MTS environment, both the ANN and random forest models performed similarly well, with the ANN outperforming the random forest for predictions on new data, however obtaining a lower $R^2$ value. Thus both the random forest and ANN models were utilised for the prediction of HVAC set points, with predictions on unseen data compared to determine the performance of each model and assess suitability for the MTO environment.

The ANN and random forest models were modified to contain the inputs and outputs displayed in Table 18.

Table 18- Inputs and outputs utilised in the development the predictive models for HVAC set point prediction

| Inputs | Outputs |
|---|---|
| Occupancy internal gains (kW) | Total building energy consumption (kW) |
| Outdoor temperature (° C) | HVAC energy consumption (kW) |
| Outdoor relative humidity (%) | Workshop air temperature (° C) |
| Outdoor wind speed (m $s^{-1}$) | Workshop relative humidity (%) |
| Cloud Cover (oktas) | Boiler Set Point |
| Manufacturing demand (kW) | Chiller Set Point |

Following model training and optimisation, the best predictive models were used to predict outputs listed in Table 18, with the predicted HVAC set points fed back into a simulation model in order to determine the energy demand of the facility with the predicted optimum set points, and to evaluate indoor conditions. Such a methodology provides a means of analytically determining optimum HVAC set points based upon manufacturing demand, outdoor weather conditions and occupancy levels, whilst maintaining humidity and temperature thresholds. This holds advantages over the manufacturing based HVAC system which requires manual specification of optimum set points, of which is time consuming and requires multiple iterations and optimisation through the use of simulation.

## 4.10 Summary

Linear regression, artificial neural networks, deep neural networks and random forests are all utilised for energy forecasting of manufacturing facilities, utilising training data generated from simulation. Such predictive techniques hold the potential to automate model development, by identifying and linking relationships in large datasets. Key metrics recommended by the ASHRAE guidelines identified the most suitable model to be applied to the prediction of optimum HVAC set points for the development of the proactive HVAC control system, and for the identification of peak energy demand.

Predicting peak demand can provide a financial incentive for companies to not only reduce their peak consumption, but also consider the implementation of tools to analyse consumption and subsequently reduce. Improving knowledge surrounding energy flows within a manufacturing environment can allow for the optimisation of both manufacturing schedules and HVAC schedules asynchronously, for a further reduction of peak demand.

# Chapter 5- Results and Discussion

## 5.1 Introduction

This chapter presents and discusses results obtained from investigations in Chapter 3 and Chapter 4. The degree-day method investigation is discussed in section 5.2, along with justification for the use of a collaborative generalised dataset. Section 5.3 compares the thermal comfort based reactive HVAC to the novel manufacturing based proactive system.

This is followed by the investigation into least squares multiple linear regression, artificial neural network, deep feed-forward neural networks and random forest predictive models investigated for applicability in this study, found in section 5.4. The chapter is concluded with the reduction of spikes in energy demand in section 5.5 and the development of the intelligent proactive manufacturing-based HVAC control system in section 5.6.

## 5.2 Degree day investigation

The applicability of the degree-day method to manufacturing facilities was investigated by determining the relationship between degree-days and building energy consumption. The degree-day method was developed primarily for determining building heating demand, but is also used to determine cooling demand and building energy consumption. The investigation considered a range of climatic conditions by analysing the four locations discussed in section 3.4.1.

The SCC was assessed to determine the relationship between degree-days and building energy consumption, as well as the relationship between manufacturing demand and building energy consumption on an hourly basis. Results were averaged over a 12-month period and are displayed in Table 19.

Table 19- Spearman Correlation Coefficient for degree-day vs energy consumption, and manufacturing schedule vs energy consumption for 4 locations

| SCC | Location | | | |
|---|---|---|---|---|
| | London | Ulyanovsk | Munich | Chicago |
| **Degree Days vs Energy** | 0.12 | 0.14 | 0.09 | 0.13 |
| **Manufacturing vs Energy** | 0.76 | 0.76 | 0.76 | 0.76 |

The investigation was repeated, looking at the energy consumption of the HVAC system alongside both degree-days and manufacturing schedule, with results for the SCC displayed in Table 20.

Table 20- Spearman Correlation Coefficient for degree day vs HVAC energy consumption, and manufacturing schedule vs HVAC energy consumption for 4 locations

| SCC | Location | | | |
|---|---|---|---|---|
| | London | Ulyanovsk | Munich | Chicago |
| **Degree Days vs HVAC Energy** | 0.12 | 0.13 | 0.08 | 0.11 |
| **Manufacturing vs HVAC Energy** | 0.75 | 0.75 | 0.75 | 0.75 |

The closer to 1 or -1 a SCC value is found to be, the closer the relationship between parameters. The relationship between degree-days and both building energy and HVAC energy consumption was negligible, with a maximum SCC of 0.14. In contrast, the relationship between manufacturing demand and both building energy and HVAC energy consumption was significant, with all SCC values above 0.75. This shows that there is little correlation between degree-days, thus outdoor weather conditions, and energy demand within the manufacturing sector. The investigation into the use of degree-days has confirmed suspicions questioning the suitability of the use of degree-day analysis for building and HVAC energy consumption for manufacturing facilities. The influence of heat gains from manufacturing equipment outweigh climatic influences in determination of building and HVAC energy, and thus HVAC requirements which are required to maintain a suitable production environment. Although climate does have an impact on the energy consumption of buildings, this cannot be used as an indicator of consumption predictions of building energy consumption or HVAC energy consumption in the industrial sector.

## 5.3 Manufacturing Based HVAC Control

### 5.3.1 MTS Scheduled Facility

Adopting the manufacturing based HVAC control (MFC) as opposed to a thermal comfort based control system (TCC) for a MTS scheduled facility resulted in a total energy saving of 7.61 % over a 12-month period. Monthly energy savings over a 12-month period can be seen in Figure 52.

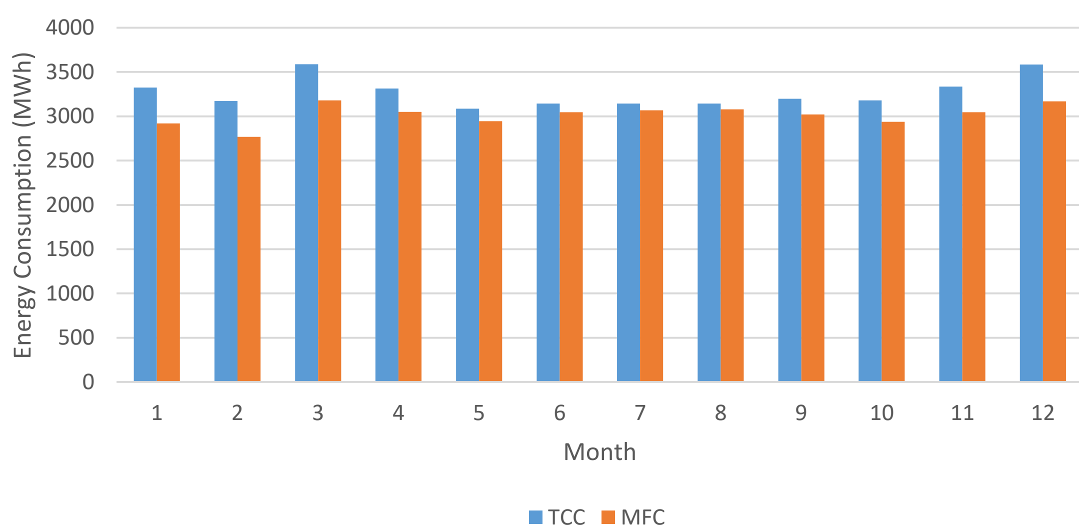



Figure 52- Total facility energy consumption based on utilising the thermal comfort and manufacturing schedule controlled HVAC system in an MTS environment

This was accompanied by a 78.9 % and 3.99 % saving in boiler and chiller systems over a 12-month period respectively (See Appendix D), along with a 16.3 % energy saving from HVAC systems. Monthly HVAC energy savings over a 12-month period can be seen in Figure 53.

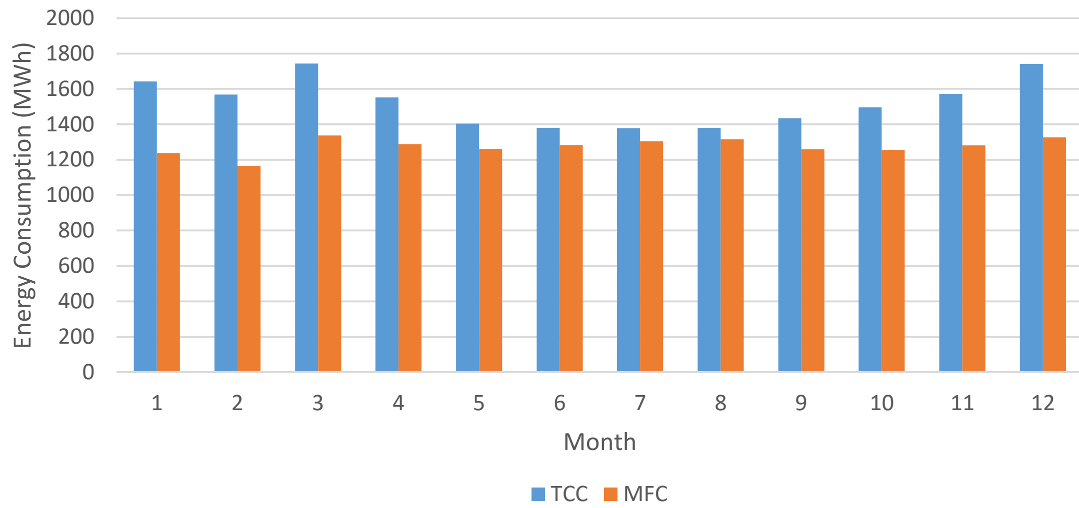



Figure 53- HVAC energy consumption based on utilising the thermal comfort and manufacturing schedule controlled HVAC system in an MTS environment

The largest HVAC system energy saving, 25.75 %, was obtained in February, with the lowest saving, 4.78 %, obtained in August.

In the cooler winter month of February, with an average outdoor temperature of 4.06 °C, the boiler systems utilised 76.4 % times less energy through the MFC approach as opposed to the TCC approach, with chiller systems utilising 6.59 % less energy.

For a typical working day in February, for the MFC approach, boiler systems were turned on prior to worker arrival in order to obtain comfortable working conditions (Figure 54). The system was subsequently turned off when conditions were met and as machining began, in anticipation of waste heat. On addition of this waste heat into the environment, chiller systems were slowly turned on after a time delay to combat excess waste heat.

In contrast, for the thermostat based TCC approach, boiler systems were only turned off once the HVAC system detected a temperature increase in the environment due to machine waste heat, which resulted in chiller systems being activated, thus for a period, both boiler and chiller systems both operated in unison. This resulted in a higher demand on the chiller system, and thus higher energy consumption.

The energy profile for the HVAC systems followed the machining profile, with a greater extent in the afternoon, once the environment and the building fabrics had reached a stable temperature.

The implementation of a manufacturing based HVAC control system allowed for a significant energy saving from the HVAC system due to the utilisation of machine waste heat as space heating. Both boiler and chiller system set points were lowered, with more efficient scheduling of both systems.

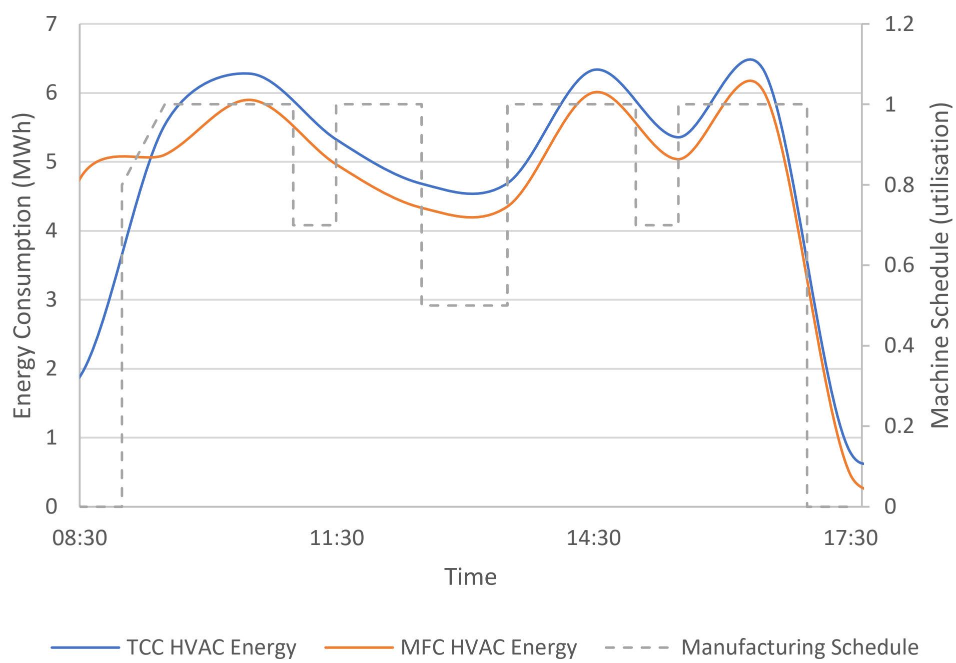



Figure 54- HVAC energy consumption for a TCC and MFC system, for a working day in February in an MTS environment, where a utilisation of 1.0 corresponds to 100% utilisation

In the warmer month of August, with an average outdoor temperature of 16.37 °C, boiler and chiller systems utilised 100 and 2.26 % less energy respectively adopting the MFC approach as opposed to the TCC approach. A lower energy saving was obtained in comparison to a cooler month, due to a greater similarity in chiller operational profiles in the warmer month. Cooling systems are energy intensive systems, with comfort cooling costing as much as one years' worth of heating for the few days that the UK reaches temperatures over 28 °C [5]. During the warmer months, the chiller systems were ultimately running constantly throughout the day to combat not only manufacturing and occupant heat gains but also solar gains. This resulted in operational profiles for the MFC and TCC cooler system that have a greater similarity than the requirements of the system in the cooler months (Figure 55).

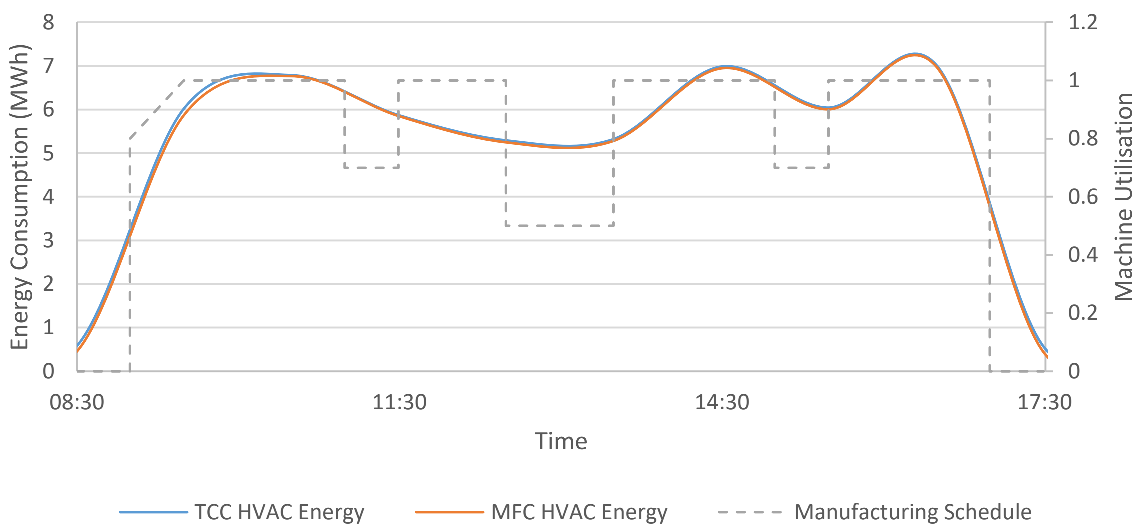



Figure 55- HVAC energy consumption for a thermal comfort controlled (TCC) and manufacturing schedule controlled (MFC) system, for a working day in August in an MTS environment, where a utilisation of 1.0 corresponds to 100% utilisation

Indoor temperature of the facility was maintained in the 19-22 °C range, with relative humidity kept below 60%.

Based on the price of fuel purchased by non-domestic consumers in 2018 [195], for a facility consuming between 20,000-69,999 MWh per year, as does the facility in this study, the total yearly savings achieved by the MFC HVAC control methodology discussed provided a saving of £324 k annually.

### 5.3.2 MTO Scheduled Facility

Adopting the MTO based manufacturing schedule regime, the implementation of a manufacturing controlled HVAC system resulted in a total facility energy saving of 14.1 % over a 12-month period. Monthly energy savings over a 12-month period can be seen in Figure 56.

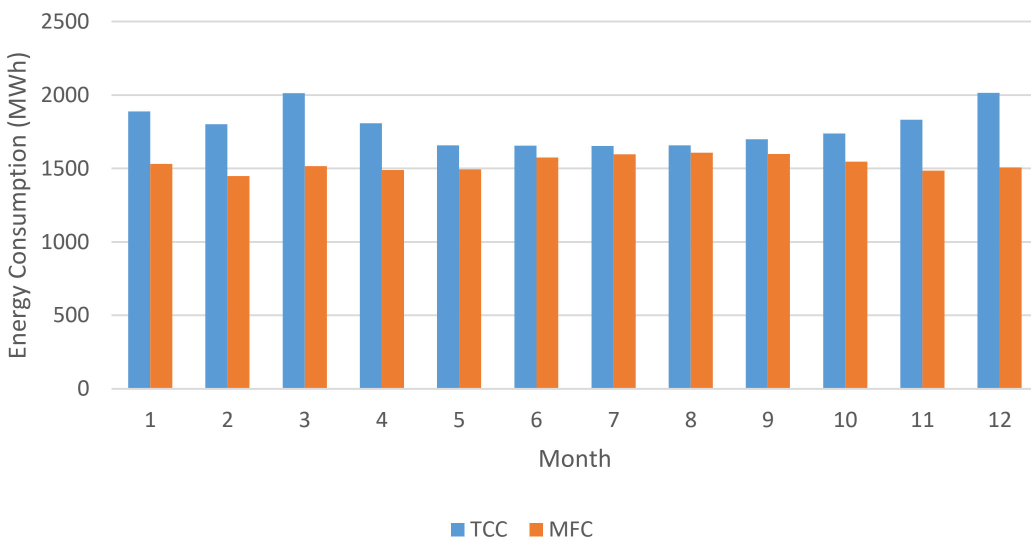



Figure 56- Total facility energy consumption for a TCC and MFC HVAC system in a MTO environment

This was accompanied by a 26.9 % saving from the HVAC system, and 86.6 % and 10.4 % saving from the boiler and chiller systems respectively (See Appendix E). Monthly energy savings over a 12-month period can be seen in Figure 57.

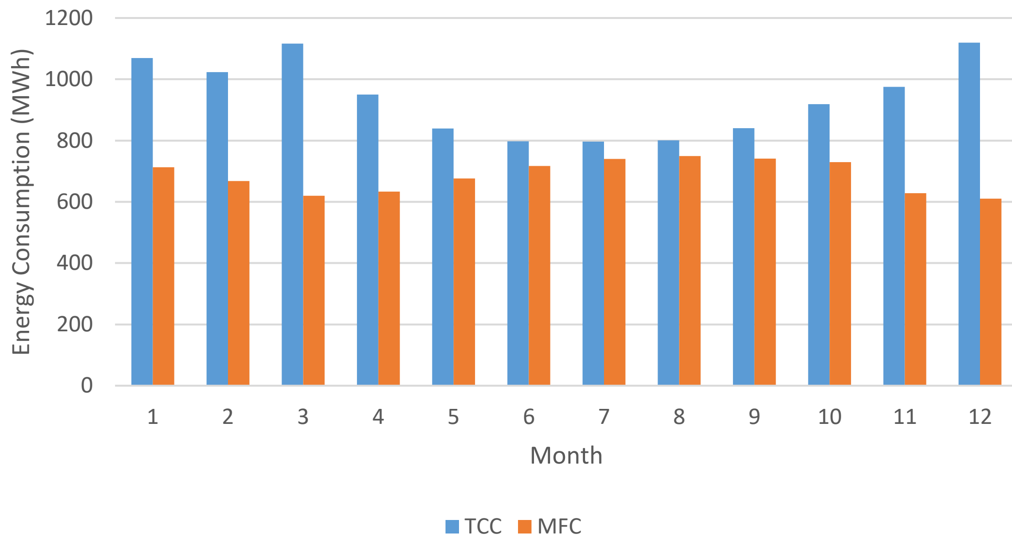



Figure 57- Total HVAC energy consumption for a TCC and MFC HVAC system in a MTO environment

Following the trend obtained from analysis of the MTS environment, the greatest energy savings from the HVAC system, 45.4 %, was obtained in the cooler month of December, with the lowest savings, 6.31 % obtained in the warmer month of August.

For the warmer month of August, with an average outdoor temperature of 16.37 °C, boiler systems were turned off as both solar and equipment heat gains provided the heat required within the space to achieve thermal comfort. Chiller systems were set to turn on progressively at the start of the working day in anticipation of machine heat gains, however the operational profile throughout the day bore a similar resemblance to that of the TCC based system, due to constant chiller requirements throughout the day to combat both excess heat from machining as well as solar heat gains, similar to that observed in analysis of the MTS environment (Figure 58). Chiller systems utilised more energy in the afternoon, not only due to a spike in manufacturing demand, but also due to residual heat in the space from the morning machining shift, and also due to the influence of solar gains. For example, a portion of shortwave radiation on building surfaces will be absorbed, raising surface temperature and giving rise to a temperature differential between inner and outer surfaces, thus driving surface conduction and time lagged thermal gains.

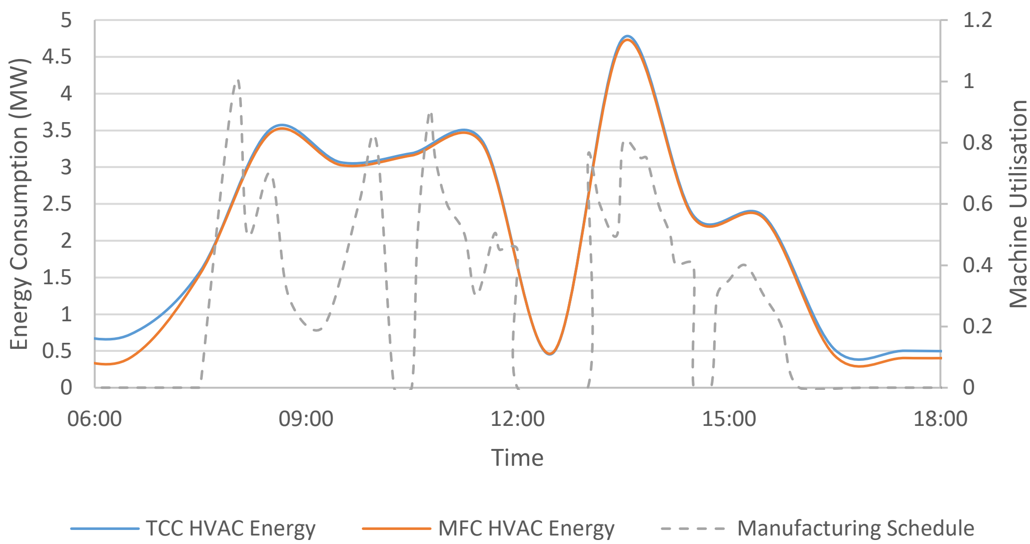



Figure 58- HVAC energy consumption for a thermal comfort controlled (TCC) and manufacturing schedule controlled (MFC) system, for a working day in August for an MTO environment, where a utilisation of 1.0 corresponds to 100% utilisation

For the month of December, with an average outdoor temperature of 4.85 °C, boiler systems were turned on slowly prior to worker arrival, in order to ensure comfortable working conditions. Chiller systems were set to an 80% operational profile when machining begun, however were instantaneously reduced to a 60% operational profile due to a morning machining lull. Chiller operation never reached 100% operational throughout the working day, due to cooler external temperatures. Systems were also set to reduce progressively at the end of the working day, in anticipation of the end of machining (Figure 59). Such operational strategies not only allowed for a reduction in energy consumption, but also a reduction in peak energy consumption from the HVAC system, a reduction of 11 %.

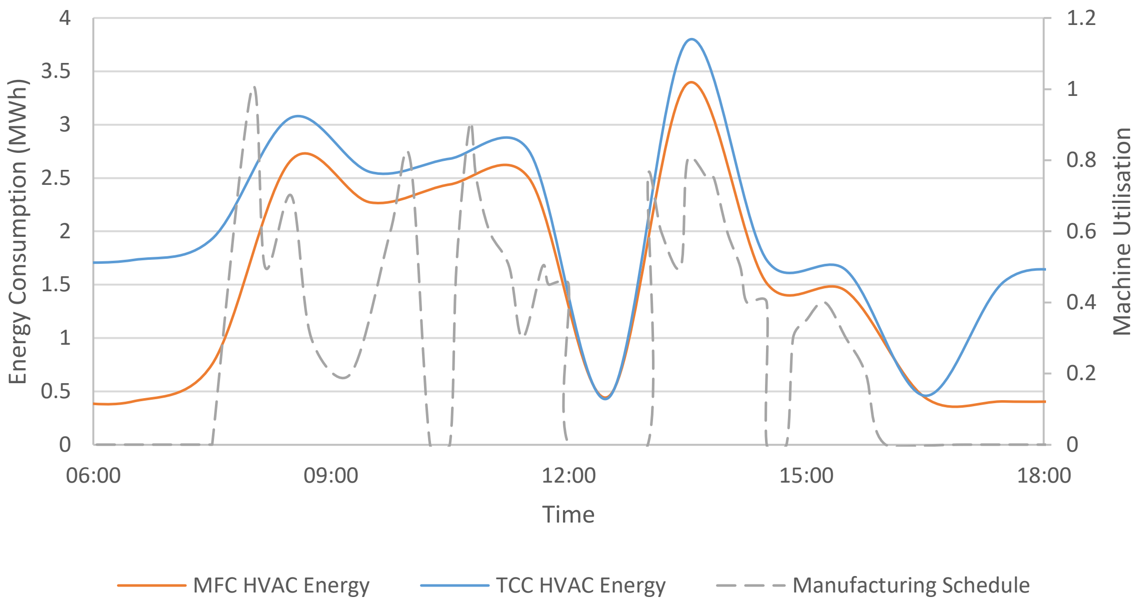



Figure 59- HVAC energy consumption for a thermal comfort controlled (TCC) and manufacturing schedule controlled (MFC) system, for a working day in December for an MTO environment, where a utilisation of 1.0 corresponds to 100% utilisation

Although the aim was to ensure a total reduction in energy consumption from the HVAC system over a working year, thus analysing data over a 24hr period, the results were also analysed excluding unoccupied hours, to determine the energy savings of the HVAC system and facility over the course of the working day. Analysis of the facility during working hours resulted in a 17.7 % energy saving from the HVAC system, 6.26 % from the building facility, 54.9% and 20.5 % saving from the boiler and chiller systems respectively.

Based on the price of fuel purchased by non-domestic consumers in 2018 [195], for a facility consuming between 20,000-69,999 MWh per year, as does the facility in this study, the yearly savings achieved by the MFC HVAC control methodology discussed provides a saving of £328 k annually.

## 5.4 Predictive Models

### 5.4.1 Least squares multiple linear regression

The LSMLR model was built for the inputs and outputs listed in Table 8, for the MTS and MTO approach. The model was provided with a month's worth of new unseen data, with errors based on new predictions displayed in Table 21, along with model accuracy metrics.

Table 21- Best LSMLR models for the MTO and MTS approach, averaged over the monthly predicted dataset

| | **Prediction Error (%)** | | | | **Accuracy Metrics** | |
|---|---|---|---|---|---|---|
| | **Building Energy** | **HVAC Energy** | **Air Temperature** | **Relative Humidity** | **R2** | **CV(RMSE) (%)** |
| **MTS** | 20.7 | 21.3 | 5.75 | 7.00 | 0.91 | 14.6 |
| **MTO** | 15.6 | 14.9 | 5.75 | 7.31 | 0.86 | 20.6 |

According to the ASHRAE guidelines [157], models are required to obtain an $R^2$ value above 0.75, and a CV(RMSE) value over 15% for monthly data, or over 30% for hourly data. In this study, CV(RMSE) and $R^2$ was calculated hourly at every time step and averaged over all analysed data points. Thus the threshold for models was set at 30% for CV(RMSE) and 0.75 for $R^2$.

Adopting the LSMLR method, both the MTS and MTO models obtained $R^2$ and CV(RMSE) values within the threshold specified by ASHRAE, with $R^2$ values of 0.91 and 0.86 for the MTS and MTO model respectively, and CV(RMSE) values of 14.6 and 20.6 % for the MTS and MTO models respectively.

However the MTS model obtained large errors, 20.7% and 21.3% for the prediction of building and HVAC energy respectively.

It was determined that the large errors in building energy and HVAC system energy were obtained at 8:30am, prior to when the manufacturing working day begun at 9:00am (Figure 60). Through the manufacturing controlled HVAC system operation, controls prior to the start of the working day were set differently to that of other times, and were not related to current manufacturing demand. The HVAC set points were set to ensure comfortable working temperatures prior to worker arrival, and in anticipation of upcoming manufacturing heat gains. Within the dataset of 12 months, this one-hour period at the start of a working day makes up 0.03% of the total dataset, and therefore more data is required in order for the model to determine the corresponding energy and HVAC system energy consumptions for this one-hour period.

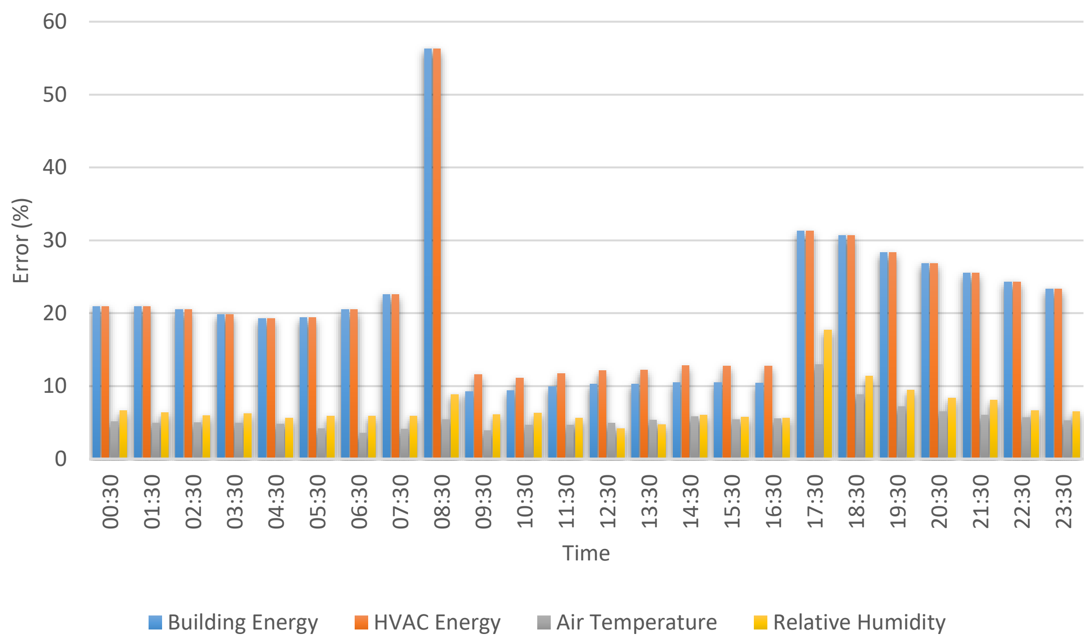



Figure 60- Hourly prediction errors for the MTS model, averaged over the monthly predicted dataset

Confidently, errors for all variables were low during occupied working hours after the error spike at 8:30am. For occupied hours, errors in building energy, HVAC energy, air temperature and relative humidity obtained average errors of 12.4, 14.3, 5.89 and 6.89 % respectively. The model was able to learn the impact of manufacturing and outdoor weather conditions on the energy consumption and indoor facility conditions. Accurate prediction of air temperature and indoor humidity during working hours is essential in order to provide data required for control of the HVAC system.

During unoccupied hours, errors were larger, with obtained errors of 23.1, 23.1, 5.43 and 7.05 % for building energy, HVAC energy, air temperature and relative humidity respectively.

For the MTO approach, again a high error of 37.5 % was obtained for HVAC energy at the start of the working day due to differences in HVAC set points (Figure 61).

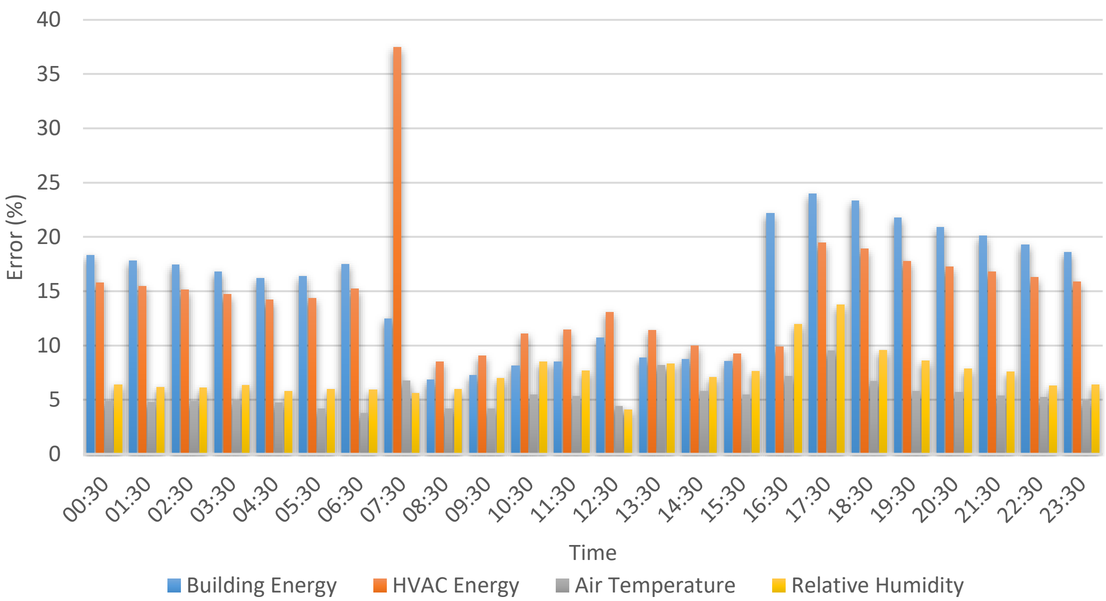


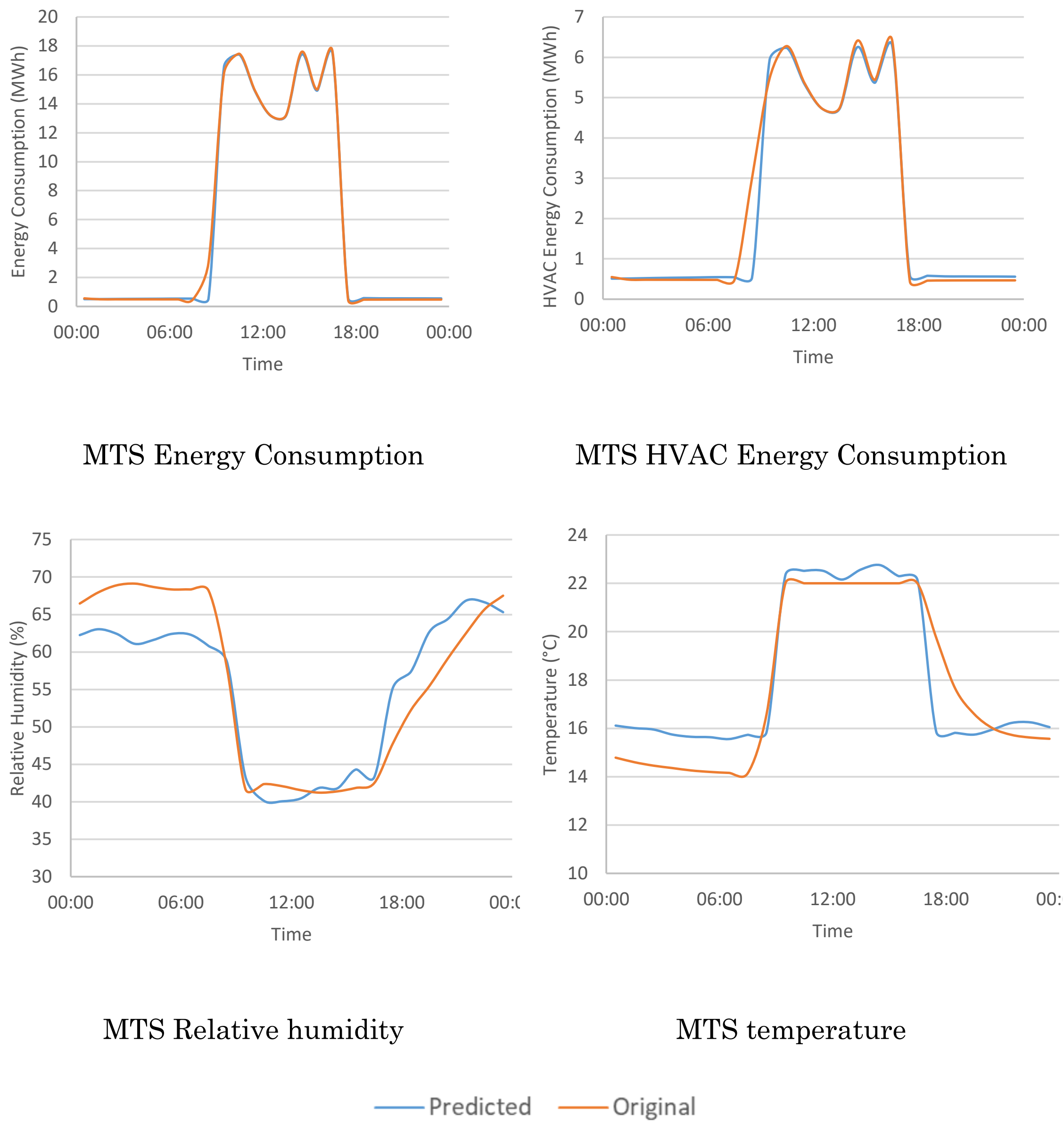

Figure 61- Hourly prediction errors for the MTO model, averaged over the monthly predicted dataset

The energy consumption, however, maintained an error below 15% for the start of the working day. Upon inspection, it was found that in contrast to the MTS approach, where all machines started at once at the start of the working day, thus spiking the energy consumption significantly, the machines in the MTO approach were not all turned on at once, and turned on gradually over a 30-minute window. Thus obtaining less of a spiked profile.

Higher errors for the prediction of building energy and HVAC energy were obtained during manufacturing facility out of hours than errors obtained for the working period. Obtaining high levels of predictive accuracy is less crucial during out of hours as air temperature and humidity predictions are not required to set optimum HVAC controls in the facility during this time. Furthermore, the use of predictive models for early identification of spikes in total building energy consumption is not required during the out of hours period, as due to the lack of machining and no occupants present, a potential spike in consumption would not occur during out of hours' time.

During unoccupied hours, errors in building energy, HVAC energy, air temperature and relative humidity obtained average errors of 19.2, 16.2, 5.40 and 7.33 % respectively. For occupied hours, average errors in building energy, HVAC energy, air temperature and relative humidity were 10.2, 13.1, 5.68 and 7.37 % respectively.

The predicted vs expected building and HVAC energy consumption, air temperature and relative humidity for one sample day from the predicted dataset is displayed in Figure 62 for the MTS environment and Figure 63 for the MTO environment.



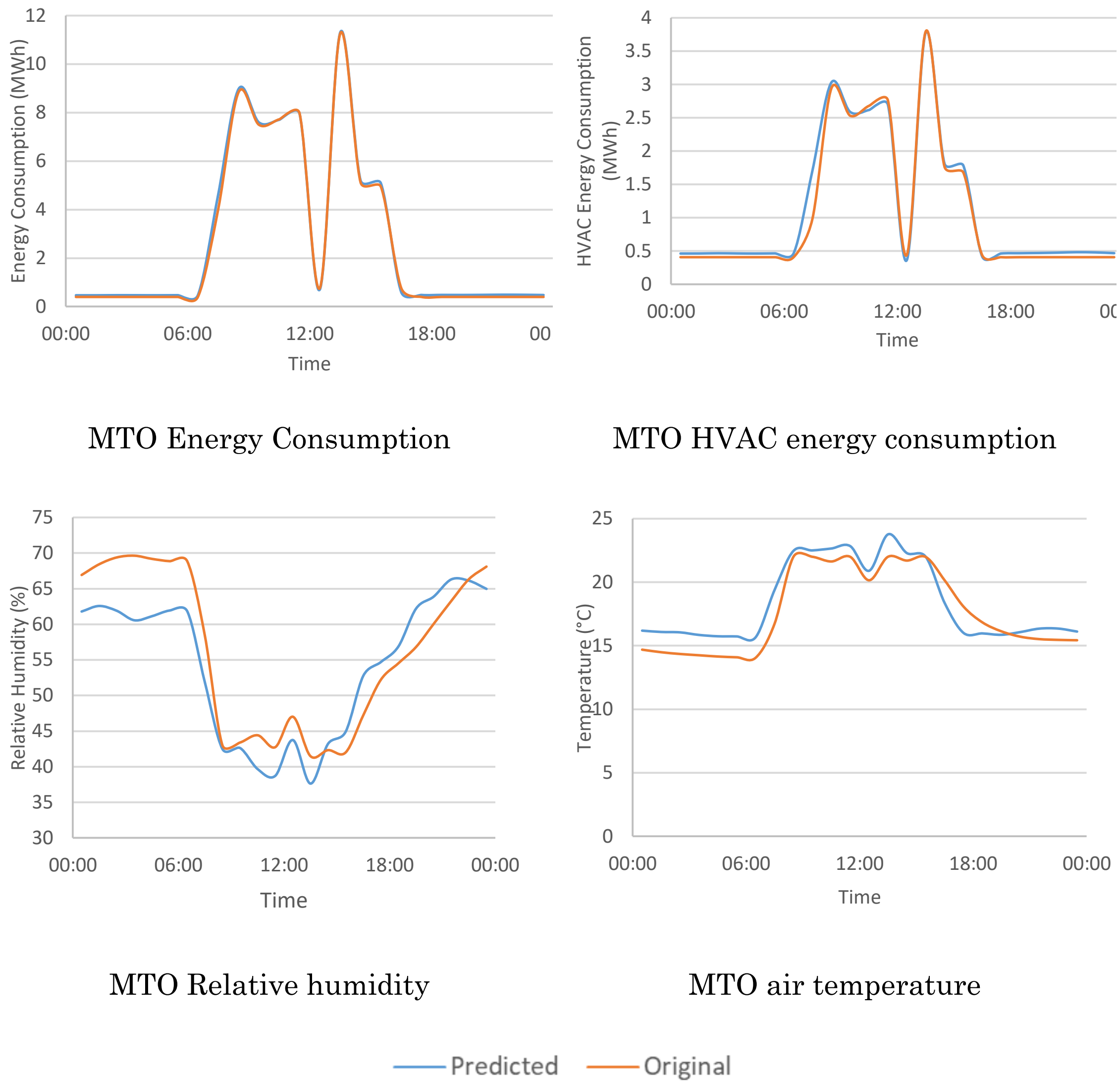

MTS Energy Consumption

MTS HVAC Energy Consumption

MTS Relative humidity

MTS temperature

Figure 62- Predicted vs expected outputs utilising the LSMLR approach for the MTS environment




MTO Energy Consumption

MTO HVAC energy consumption

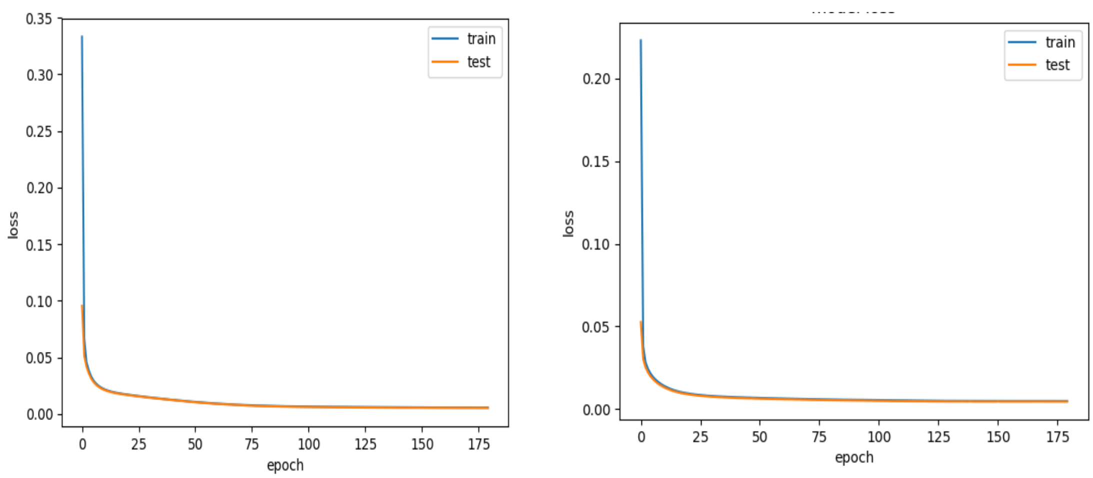
MTO Relative humidity

MTO air temperature

Figure 63- Predicted vs expected outputs utilising the LSMLR approach for the MTO environment

### 5.4.2 Artificial Neural Networks

As discussed in section 4.5, an optimisation algorithm is used to change weights in order to obtain a lower error, and navigate down a gradient of error. The function used to evaluate a solution obtained from the optimisation algorithm, such as a set of weights, is the loss function. It is therefore essential to monitor the loss throughout the training process of a neural network in order to ensure that the loss is decreasing with each iteration through the training process. The loss curves plotted for the final MTO and MTS ANN models display a good fit due to the decrease of loss to a point of stability (Figure 64).




MTO loss MTS loss

Figure 64- Loss vs Epoch for the MTO and MTS environments

The accuracy metrics and errors based on predictions on an unseen data set for the highest performing ANN models for the MTS and MTO approach are displayed in Table 22.

Table 22- Best ANN models for the MTO and MTS approach, averaged over the monthly predicted dataset

| | Prediction Error (%) | | | | Accuracy Metrics | |
|---|---|---|---|---|---|---|
| | **Building Energy** | **HVAC Energy** | **Air Temperature** | **Relative Humidity** | **R2** | **CV(RMSE) (%)** |
| **MTS** | 11.0 | 12.4 | 4.27 | 6.38 | 0.93 | 17.4 |
| **MTO** | 12.8 | 11.2 | 4.63 | 6.06 | 0.90 | 28.1 |

Both the MTS and MTO model obtained $R^2$ and CV(RMSE) values within the ASHRAE guideline thresholds. The CV(RMSE) score for the MTO model is relatively high at 28.1 % in comparison to the CV(RMSE) for the MTS model at 17.4%. RMSE was calculated for each output parameter, and it was found that the prediction of HVAC energy obtained a high RMSE value for the MTO model, thus impacting the final CV(RMSE) value.

Errors in predictions made for building energy, HVAC energy, air temperature and relative humidity for the MTO ANN model, Figure 65, follows the trend in errors made on predictions using the LSMLR MTO model (Figure 61).

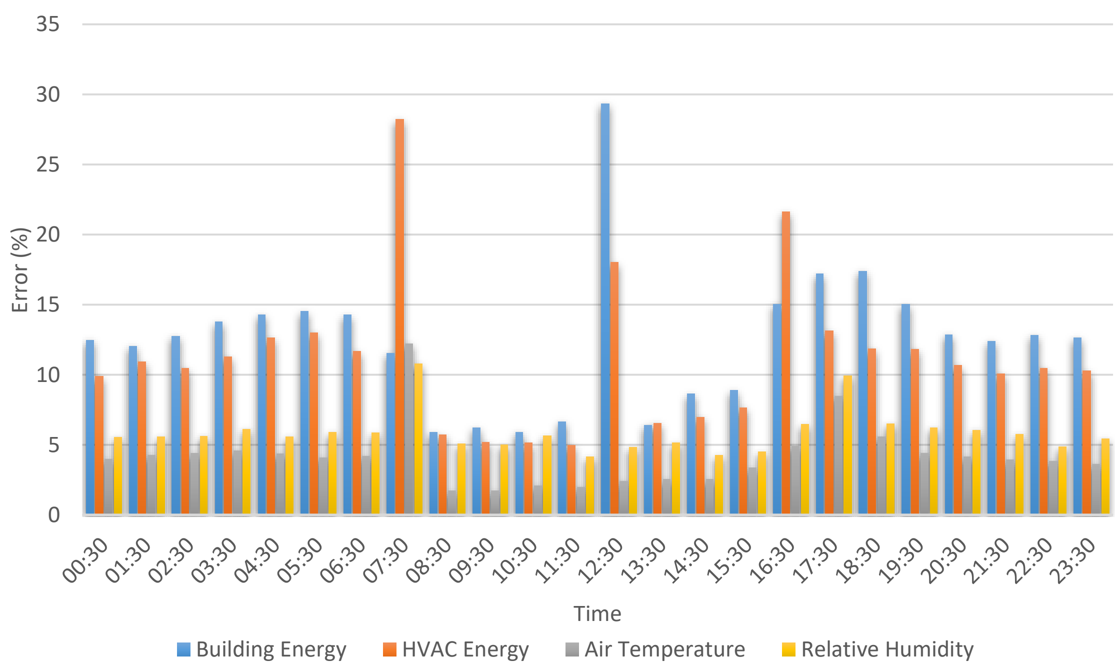



Figure 65- Hourly error between predicted and expected results for the MTO model, averaged over the monthly predicted dataset

Higher errors were obtained for prediction of building and HVAC energy, 29.4 and 18.0 % respectively, during the lunch break (12:30pm), as similar to the lack of data regarding the start of the working day, the sudden reduction in production over the lunch break and thus reduction in energy demand makes up only 0.03% of the total dataset. Prediction errors for air temperature and relative humidity however remained low, < 5.0 %, as such variables did not fluctuate greatly over this hour, unlike the building and HVAC energy consumption. For the MTO model, during unoccupied hours, errors in building energy, HVAC energy, air temperature and relative humidity obtained average errors of 13.9, 11.3, 4.57 and 6.08 % respectively.

Similarly, Arendt et al. [196] obtained higher errors for predictions of overnight air temperature within a building due to low variability in temperature, and stated a weakness of feed-forward ANN being the lack of the notion of dynamics.

For occupied hours, average errors in building energy, HVAC energy, air temperature and relative humidity were 10.5, 11.0, 3.55 and 5.59 % respectively.

Similarly, predictions using the ANN model for the MTS approach showed high errors for building and HVAC energy consumption, 54.9 and 55.2 % respectively, at the start of the working day (Figure 66).

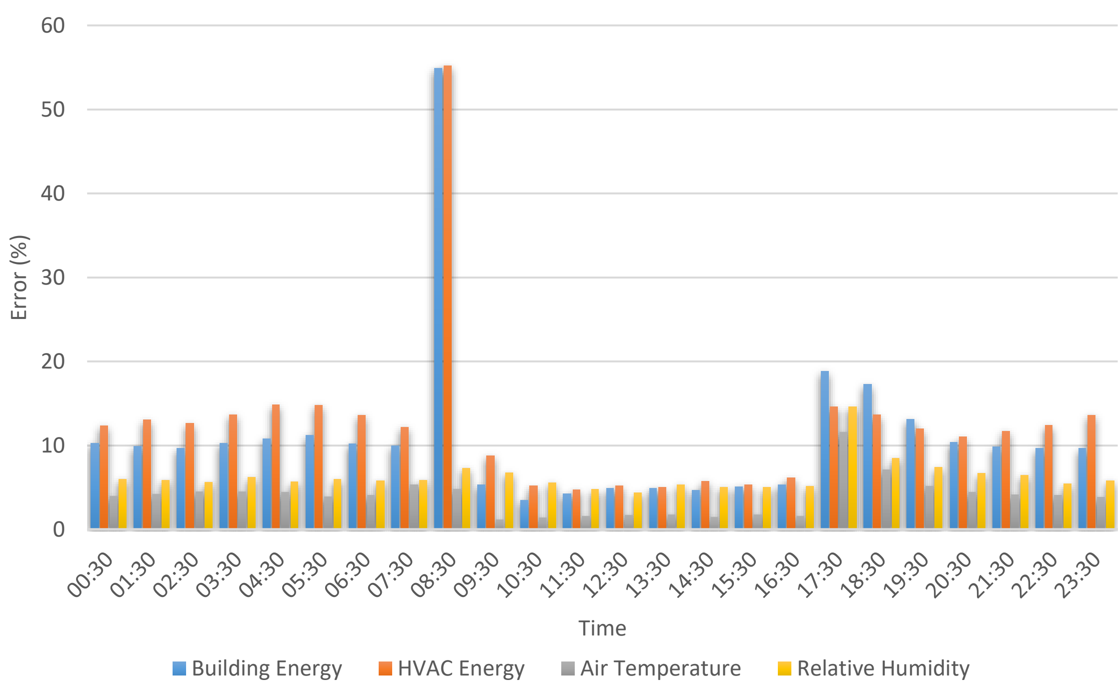


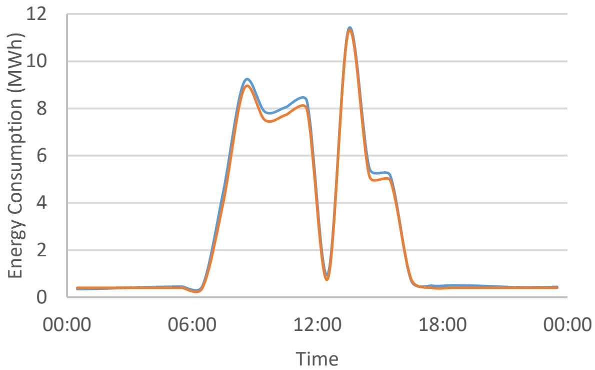

Figure 66- Hourly error between predicted and expected results for the MTS model, averaged over the monthly predicted dataset

Such a trend in predictive error is consistent with that of the LSMLR model for the MTS approach. The ANN did not return large errors for the prediction of building and HVAC energy for the MTS approach over the lunch period (errors of 4.87 and 5.83 % respectively). Upon inspection of machining schedules, for the MTS approach, a more continuous manufacturing operation than the MTO approach, machines continued to operate over the lunch period, and thus the energy demand did not fluctuate to as great of an extent (Figure 68). Errors in prediction for air temperature and relative humidity remained low throughout the working day, less than 7.5 %. Such results are promising, as HVAC set points are dependent upon levels of relative humidity and air temperature in the facility, thus accurate prediction of these variables enable optimum HVAC set points to be determined.

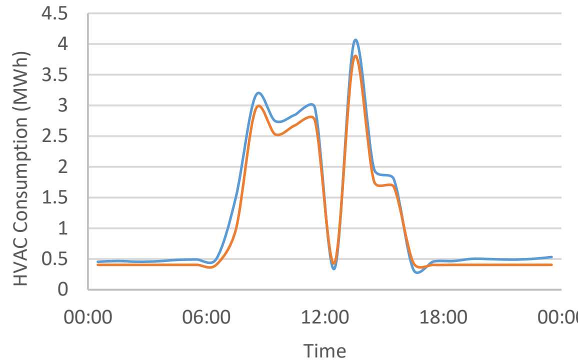
For the MTS model, during unoccupied hours, errors in building energy, HVAC energy, air temperature and relative humidity obtained average errors of 10.9, 13.0, 4.54 and 6.23 % respectively. For occupied hours, average errors in building energy, HVAC energy, air temperature and relative humidity were 11.2, 11.6, 2.87 and 6.38 % respectively.

The predicted output variables can be seen against expected values for the MTO and MTS in Figure 67 and Figure 68 respectively. The ANN was able to accurately predict trends in data, as well as quantitatively determine energy consumption and indoor conditions.

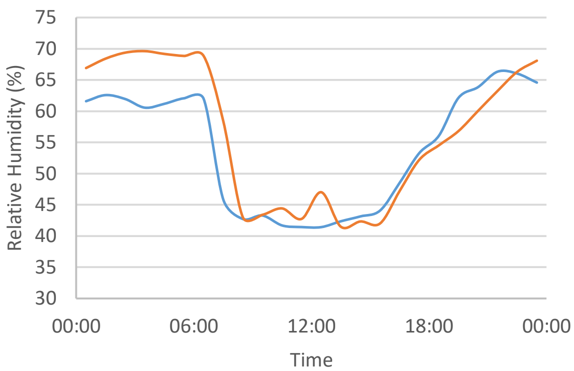
Similar to the results obtained with the LSMLR model, the ANN was able to predict building energy consumption, HVAC energy consumption, air temperature and relative humidity to a higher level of accuracy during occupied hours. Obtaining high levels of predictive accuracy during working hours is more crucial in order to determine optimum HVAC set points and identify spikes in energy consumption, as well as ensuring thermal comfort requirements for occupants are met.



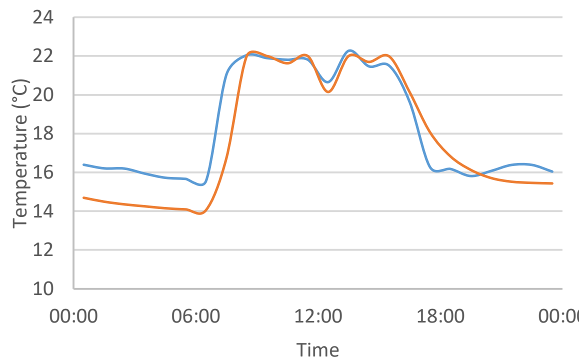

MTO Building Energy




MTO HVAC Energy




MTO Relative Humidity




MTO Air Temperature

Predicted Original

Figure 67- Predicted vs expected outputs utilising the ANN approach for the MTO environment

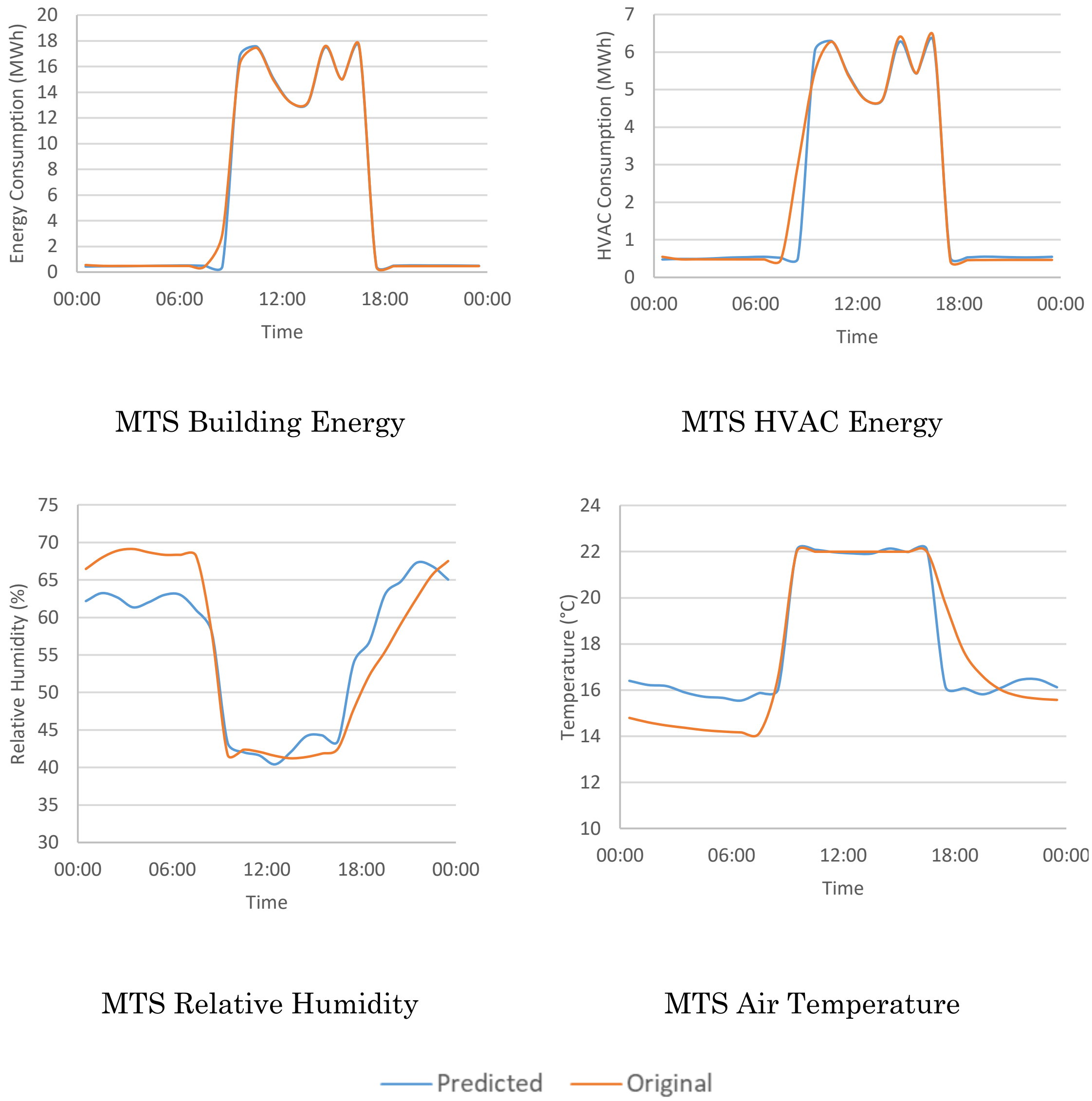
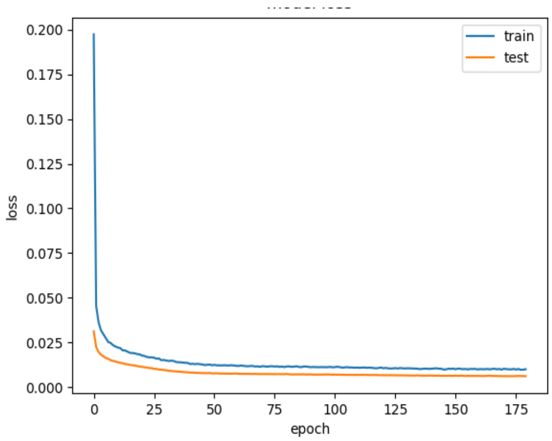
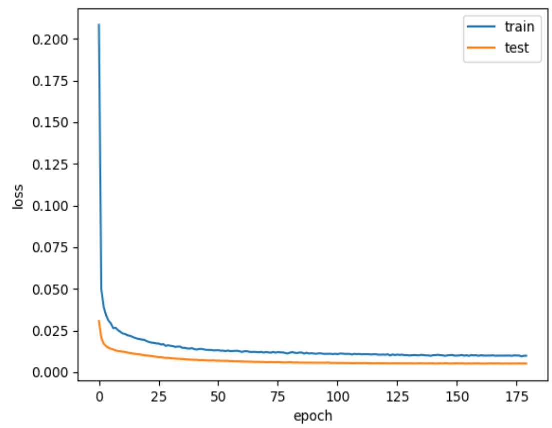



Figure 68- Predicted vs expected outputs utilising the ANN approach for the MTS environment

### 5.4.3 Deep Neural Networks

Loss curves were plotted for the DNNs to ensure the loss was decreasing with each iteration of the training process. The loss curves plotted for the final MTO and MTS DNN models display a good fit due to the decrease of loss to a point of stability (Figure 69).




MTO loss MTS loss

Figure 69- Loss curves for DNN models

The accuracy metrics and errors based on predictions on an unseen data set for the best DNN models for the MTS and MTO approach are displayed in Table 23.

The use of DNN for the prediction of building and HVAC energy consumption produced high errors, 36.6 and 20.9 % respectively, for the MTS approach. Similarly, the MTO approach obtained errors of 33.8 and 15.5 % respectively (Table 23).

Table 23- Best DNN models for the MTO and MTS approach

| | Prediction Error (%) | | | | Accuracy Metrics | |
|---|---|---|---|---|---|---|
| | **Building Energy** | **HVAC Energy** | **Air Temperature** | **Relative Humidity** | **R2** | **CV(RMSE) (%)** |
| **MTS** | 36.6 | 20.9 | 4.53 | 6.88 | 0.92 | 19.32 |
| **MTO** | 33.8 | 15.5 | 4.83 | 6.93 | 0.89 | 31.5 |

Both the MTO and MTS models were able to predict air temperature and relative humidity to a high accuracy of less than 7.0 %.

However the MTO model obtained a CV(RMSE) value of 31.5 %, above that of the threshold of 30 % set for model calibration by the ASHRAE guide. Therefore, overall, the model cannot reliably be used to provide accurate predictions.

Both the MTS (Figure 70) and MTO (Figure 71) models obtained a high error of 57.6 % and 28.4 % for building energy consumption, and errors of 55.7 % and 45.6 % for HVAC energy consumption at the start of the working day, similar to that seen with predictions made with the LSMLR and ANN models.

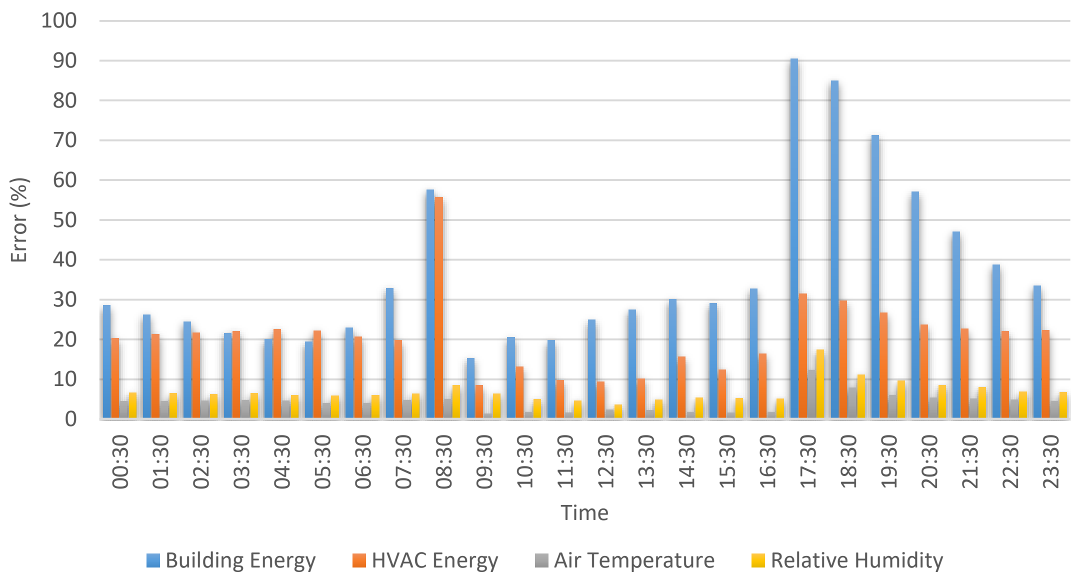



Figure 70- Hourly prediction errors for the MTS model, averaged over the monthly predicted dataset

More data is required in order to produce a dataset which contains more entries reflecting this hour of the working day. Likewise, the MTO model obtained a higher error for HVAC energy, 45.6 %, at this time.

For the MTS model, during unoccupied hours, errors in building energy, HVAC energy, air temperature and relative humidity obtained average errors of 39.1, 24.9, 4.94 and 7.29 % respectively. For occupied hours, average errors in building energy, HVAC energy, air temperature and relative humidity were 32.2, 14.1, 2.95 and 6.39 % respectively.

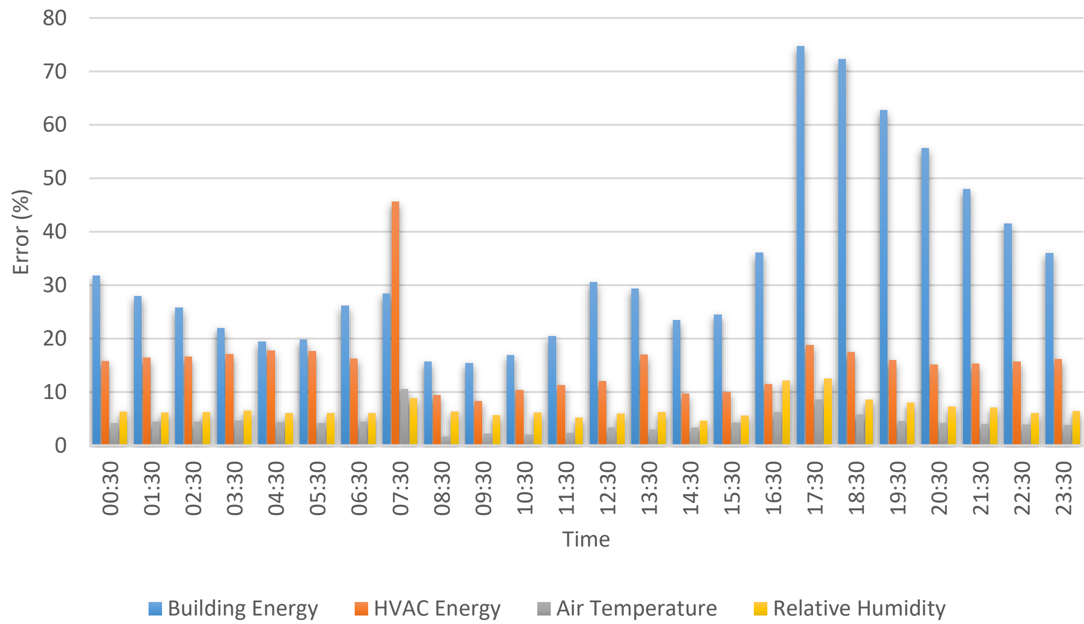



Figure 71- Hourly prediction errors for the MTO model, averaged over the monthly predicted dataset

Both the MTS and MTO obtained high errors for building energy consumption after the working day, both of which decreased into the evening. The DNN overestimated the energy demand in comparison to the expected demand. Due to the manufacturing based HVAC controls, energy demand for the HVAC system for non-working hours was lower than what would have been expected if the facility was operating or if thermal comfort condition thresholds were required. Therefore, a greater energy demand was predicted as the model was not able to determine that thermal comfort thresholds were not required at this time.

The model was thus not able to accurately learn the impact of manufacturing demand and operation along with the influence of occupants in the building.

During unoccupied hours, errors in building energy, HVAC energy, air temperature and relative humidity obtained average errors of 40.2, 16.6, 4.66 and 7.08 % respectively. For occupied hours, average errors in building energy, HVAC energy, air temperature and relative humidity were 24.1, 14.5, 3.88 and 6.66 % respectively.

Although errors for the building energy consumption and HVAC energy consumption were high, the DNN models were able to predict the general trend of energy consumption for the MTS and MTO approach (Figure 72 and Figure 73 respectively).

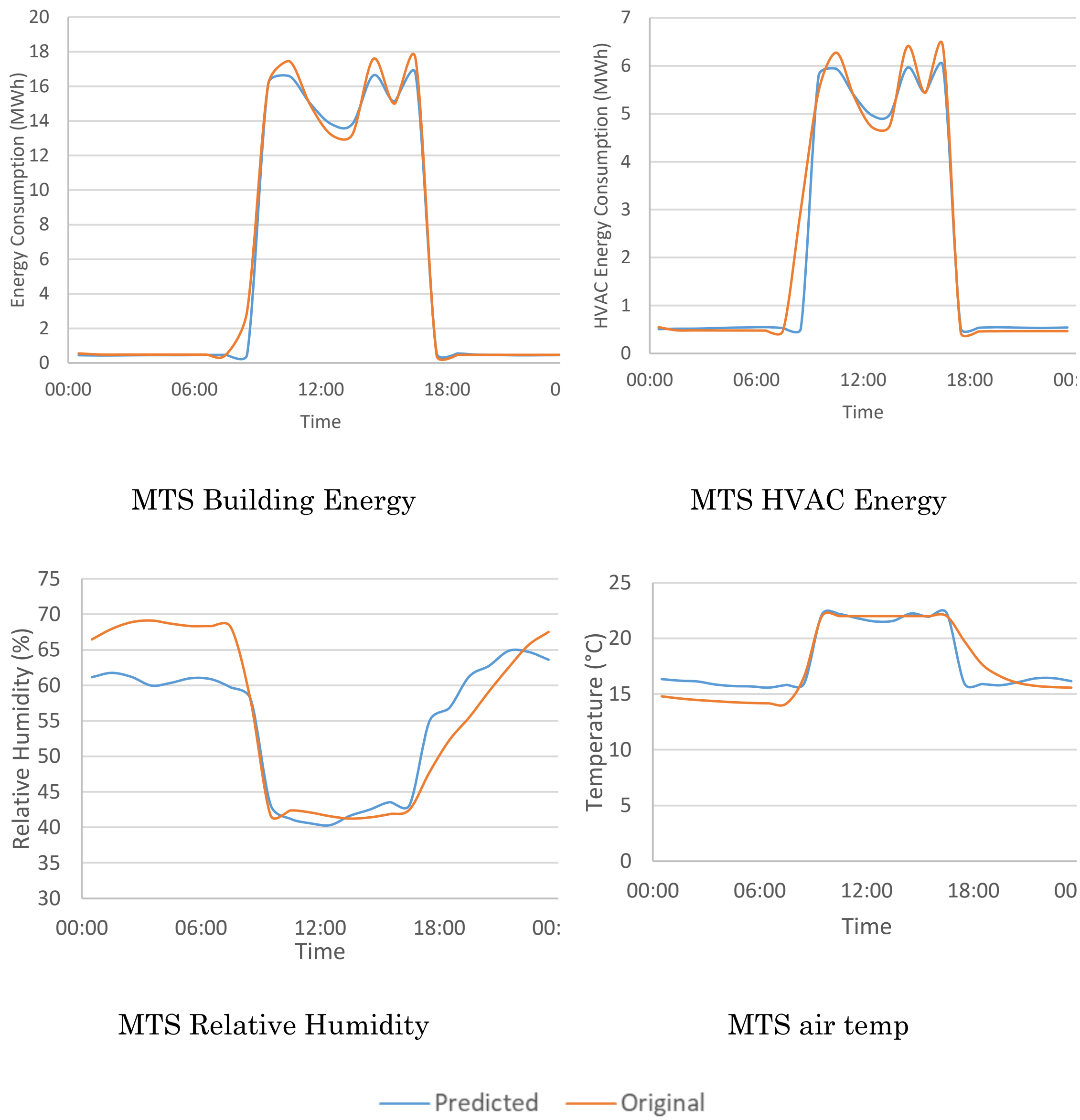



Figure 72- Predicted vs expected outputs utilising the DNN approach for the MTS environment

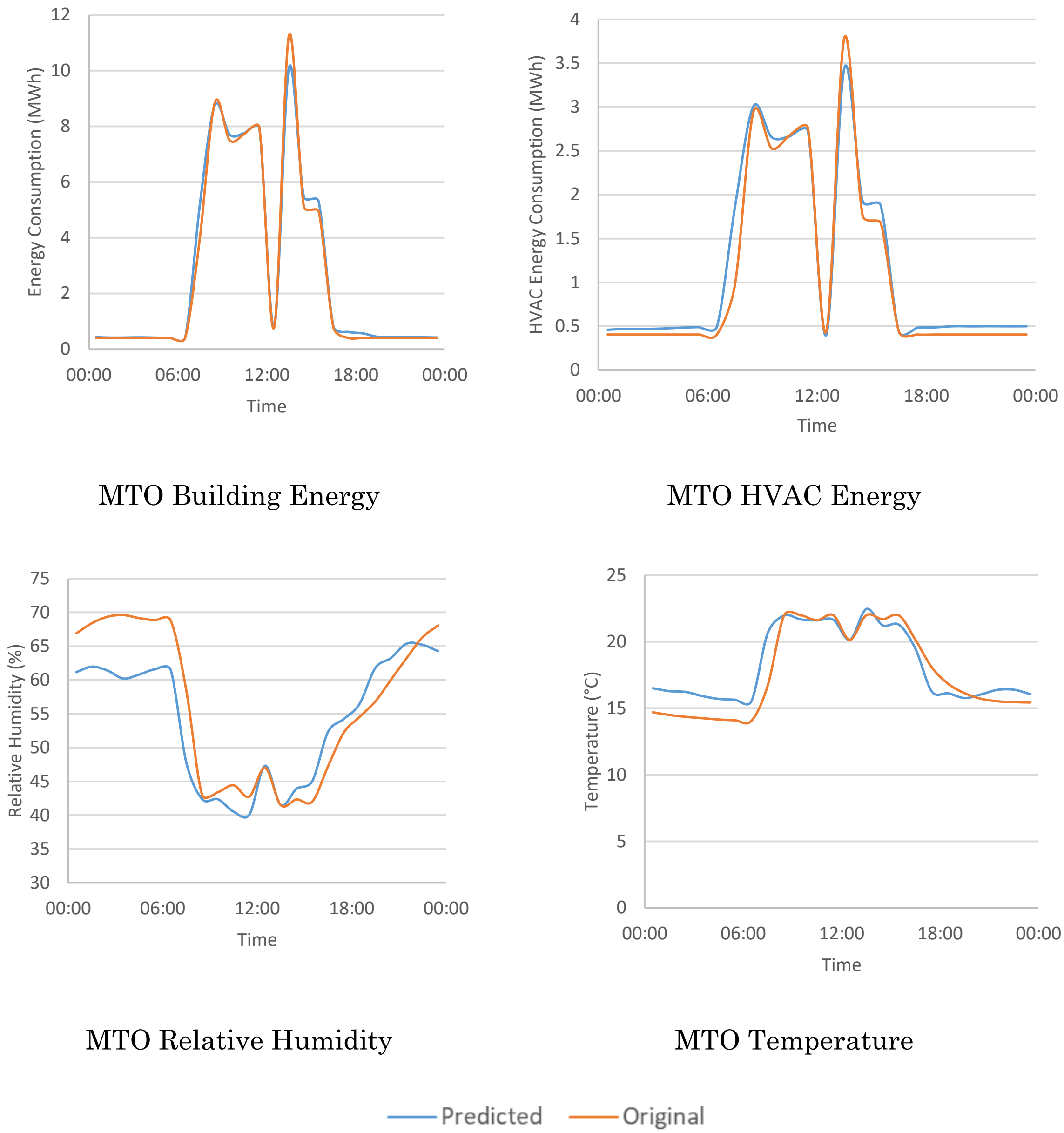



Figure 73- Predicted vs expected outputs utilising the DNN approach for the MTO environment

The DNN was concluded to be an effective tool for determining energy trends, as well as for the accurate prediction of air temperature and relative humidity for the MTO and MTS approach. However the DNN model was not able to reliably predict building and HVAC energy consumption to an appropriate degree of accuracy, and thus is not an effective tool for predicting spikes in energy consumption or prediction of energy use for financial purposes.

### 5.4.4 Random Forest

The random forest models developed in section 4.7 were used to predict outputs based on a months' worth of unseen data, with results displayed in Table 24, alongside model accuracy metrics.

Table 24- Prediction errors and accuracy metrics for the final random forest model for the MTS and MTO approach

| | Error (%) | | | | Accuracy Metric | |
|---|---|---|---|---|---|---|
| | **Building Energy** | **HVAC Energy** | **Air Temperature** | **Relative Humidity** | **R2** | **CV(RMSE) (%)** |
| **MTS** | 13.9 | 14.2 | 4.35 | 7.51 | 0.94 | 11.2 |
| **MTO** | 3.48 | 4.40 | 4.32 | 7.60 | 0.92 | 14.0 |

Both the MTS and MTO models accuracy metrics were well within the threshold for acceptable models set in the ASHRAE guidelines, with the $R^2$ scores being 0.94 and 0.92 and the CV(RMSE) scores being 11.2 and 14.0 % for the MTS and MTO models respectively. The MTO model performed highly, with a low error of 3.48 % for the prediction of building energy demand.

Following similar trends set by the LSMLR, ANN and DNN models, use of the random forest model resulted in high errors of 55.9 % for the prediction of building and HVAC energy at the start of the working day for the MTS model (Figure 74).

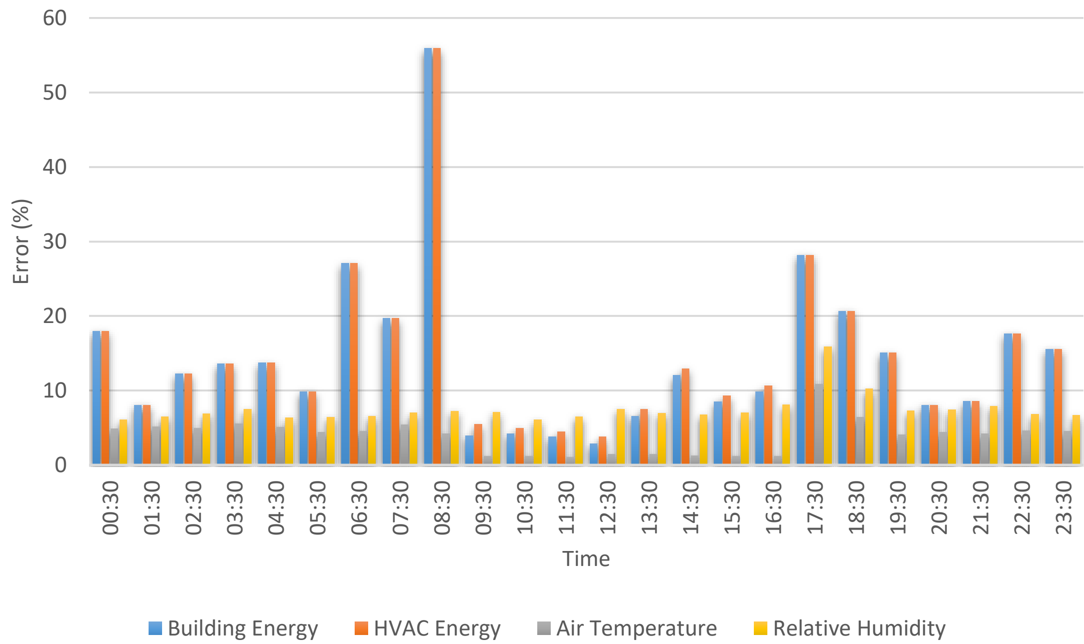



Figure 74- Hourly prediction errors for the MTS model, averaged over the monthly predicted dataset

Errors remained low for all variables throughout the working day, less than 13 %, which shows the model was able to determine the impact of manufacturing demand and occupancy levels on the thermal energy flows within the building. Higher errors were obtained at the end of the working day, 28.2 %, for building energy and HVAC energy. The model predicted a higher energy consumption than expected for this time. No occupants or machining were occurring during this time, and therefore such an error may have occurred due to fluctuating outdoor weather conditions.

For the MTS model, during unoccupied hours, errors in building energy, HVAC energy, air temperature and relative humidity obtained average errors of 14.8, 14.8, 4.86 and 7.11 % respectively. For occupied hours, average errors in building energy, HVAC energy, air temperature and relative humidity were 13.6, 14.3, 2.51 and 7.92% respectively.

The MTO showed low errors at all times, less than 14 % for all variables (Figure 75). A higher error was obtained for HVAC energy consumption at the start of the working day, which is consistent with the results obtained from the LSMLR, ANN and DNN models, due to a soft start approach to machine start up in contrast to the MTS approach. Predictions for relative humidity showed the greatest errors throughout the course of the working day.

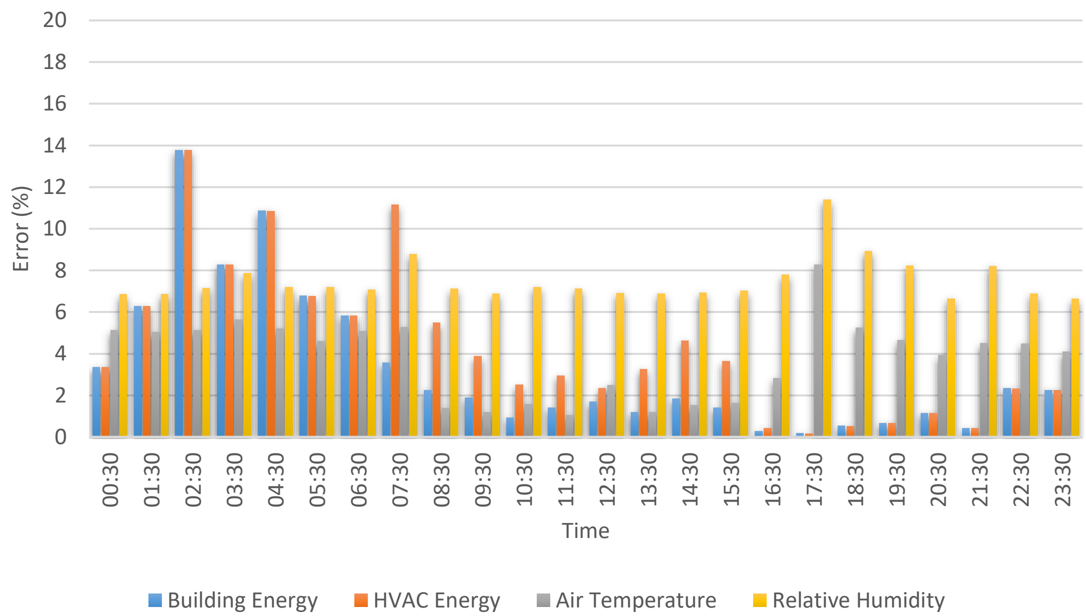



Figure 75- Hourly prediction errors for the MTO model, averaged over the monthly predicted dataset

For the MTO model, during unoccupied hours, errors in building energy, HVAC energy, air temperature and relative humidity obtained average errors of 4.48, 4.47, 5.07 and 7.65 % respectively. For occupied hours, average errors in building energy, HVAC energy, air temperature and relative humidity were 1.65, 4.02, 2.02 and 7.26 % respectively.

The random forest models were able to predict the general trend of energy consumption for the MTS and MTO approach, as well as predict variables with a high accuracy (Figure 76 and Figure 77 respectively). The random forest models for the MTO and MTS approaches however predicted relative humidity to fluctuate to a greater extent than that measured in simulation. Such fluctuations however were never greater than 10%, and relative humidity remained within the threshold required for thermal comfort.

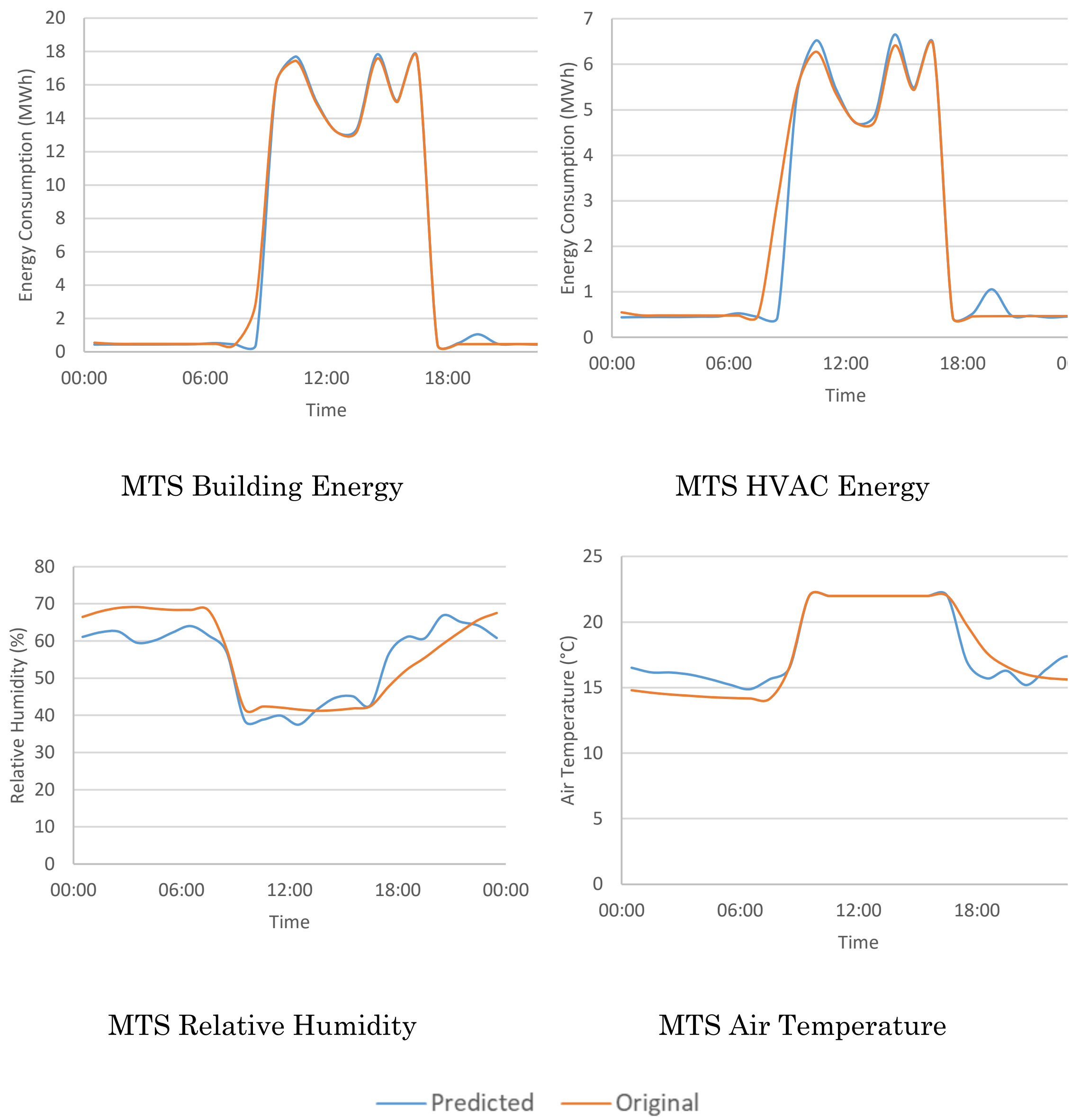



Figure 76- Predicted vs expected outputs utilising the Random Forest approach for the MTS environment

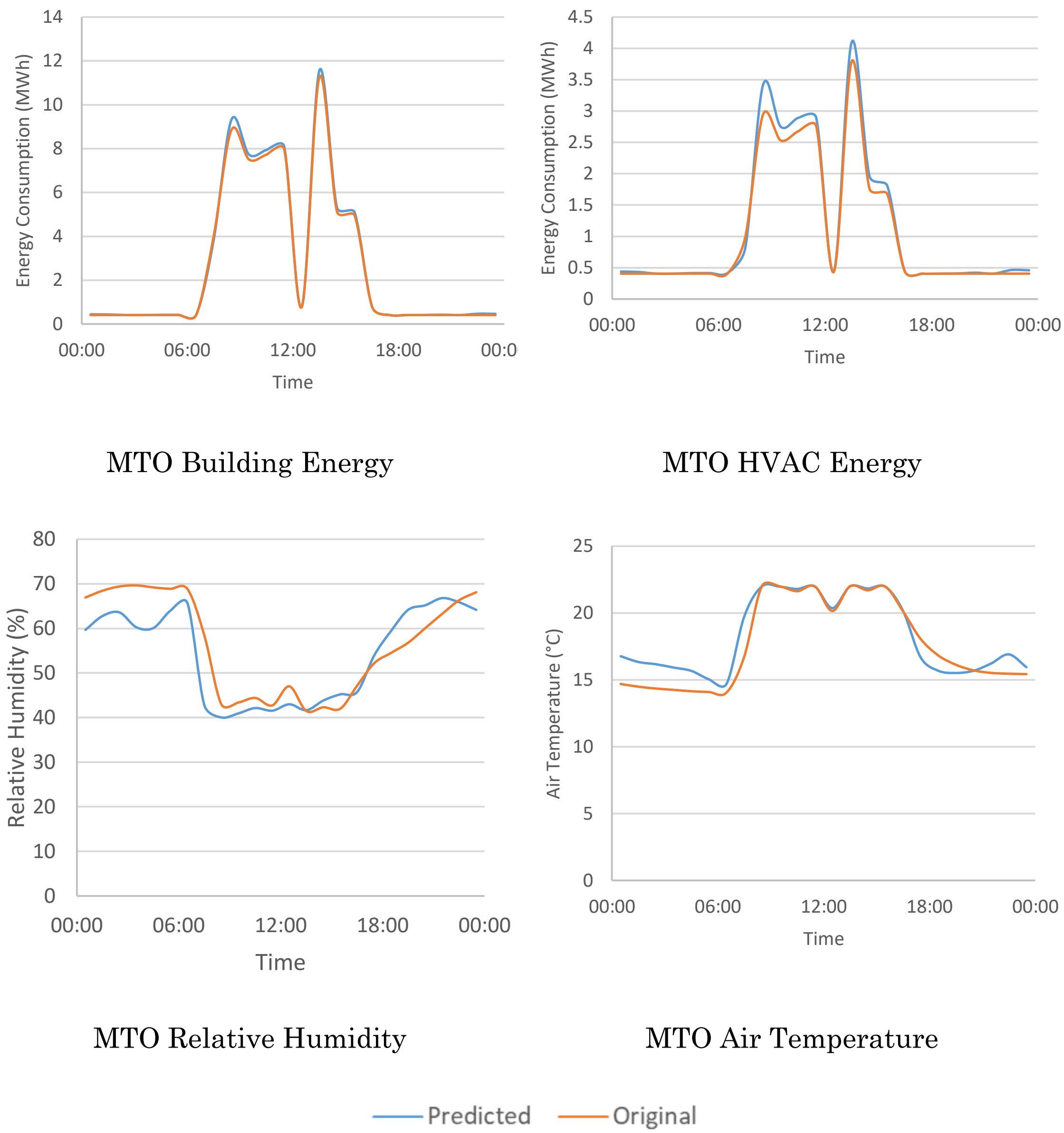



Figure 77- Predicted vs expected outputs utilising the Random Forest approach for the MTO environment

The performance of both the MTS and MTO random forest models displays the capability and potential for such a model for the prediction of building and HVAC demand, along with air temperature and relative humidity. Such models can be reliably used for the prediction of potential spikes in energy consumption, as well as requirements for HVAC systems in order to maintain optimum indoor conditions for thermal comfort.

### 5.4.5 Predictive Models Results Summary

Approaches were optimised in section 4.4, 4.5, 4.6 and 4.7, with the best model for each predictive model approach displayed in Table 25 and Table 26 for the MTS and MTO approach respectively.

Table 25- Summary of predictive models for the MTS approach

| MTS | Prediction Error (%) | | | | Accuracy Metrics | |
|---|---|---|---|---|---|---|
| | Building Energy | HVAC Energy | Air Temperature | Relative Humidity | R2 | CV(RMSE) (%) |
| LSMLR | 20.7 | 21.3 | 5.75 | 7.00 | 0.91 | 14.6 |
| ANN | 11.0 | 12.4 | 4.27 | 6.38 | 0.93 | 17.4 |
| DNN | 36.6 | 20.9 | 4.53 | 6.88 | 0.92 | 19.32 |
| Random Forest | 13.9 | 14.2 | 4.35 | 7.51 | 0.94 | 11.2 |

Table 26- Summary of predictive models for the MTO approach

| MTO | Prediction Error (%) | | | | Accuracy Metrics | |
|---|---|---|---|---|---|---|
| | Building Energy | HVAC Energy | Air Temperature | Relative Humidity | R2 | CV(RMSE) (%) |
| LSMLR | 15.6 | 14.9 | 5.75 | 7.31 | 0.86 | 20.6 |
| ANN | 12.8 | 11.2 | 4.63 | 6.06 | 0.90 | 28.1 |
| DNN | 33.8 | 15.5 | 4.83 | 6.93 | 0.89 | 31.5 |
| Random Forest | 3.48 | 4.44 | 4.32 | 7.63 | 0.92 | 14.0 |

All models performed to the level of accuracy required by the ASHRAE guidelines, with an $R^2$ value of greater than 0.75 and a CV(RMSE) value of less than 30%, with the exception of the DNN model for the MTO environment, which obtained a CV(RMSE) value of 31.5 %.

Results show that all models have the potential for energy and condition prediction in the manufacturing sector, with all models able to learn the pattern of variables and determine relationships between the input and outputs variables. Some models however, cannot be reliably be used to quantitatively predict required variables due to high error, such as the DNN models for both MTS and MTO environment, and thus these techniques are only suited to prediction of trends and patterns. The use of DNN increases the complexity of the model compared to a neural network with a single hidden layer, which requires a large amount of data in order to perform well along with extensive training. The use of a DNN is therefore not suited to the problem in this study, due to the dataset size and limitations in computational capacity for extensive model training.

More suitably, the ANN and Random Forest models performed highly for the MTS environment, with the Random Forest outperforming all models for the MTO approach. The accurate prediction of building energy demand allows for early identification of costly spikes in energy consumption, and the prediction of indoor conditions allows optimum HVAC conditions to be set whilst ensuring a comfortable thermal environment is maintained for workers as well as production specific environmental conditions.

## 5.5 Energy Demand Peak Reduction

The synchronous optimisation of the manufacturing and HVAC schedule discussed in section 4.8 allowed for a 15.1 % reduction in peak energy demand over the course of a working day (Figure 78). For comparison, machine production and energy consumption was kept as a constant throughout the optimisation process with negligible change to both parameters (0.07% and 0.15% increase in energy consumption and productivity for the optimised approach respectively).

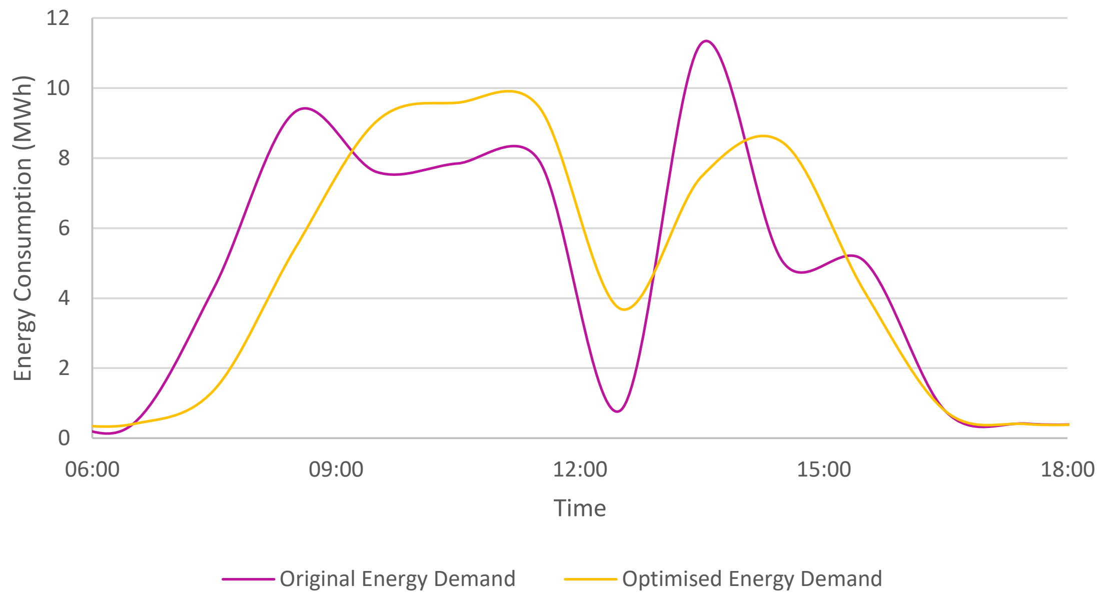



Figure 78- Original vs optimised energy consumption due to manufacturing and HVAC schedule modification

The original highest energy peak at hour 13:30, coinciding to the start of the afternoon shift, was avoided by maintaining a certain level of machining throughout the lunch hour. This maintained a more constant thermal environment throughout the facility workshop, and avoided the need for fluctuations in HVAC control due to avoiding a rapid increase in machining and machining waste heat when work resumed after the lunch period, as well as allowing for reduced machining in the afternoon without a compromise on productivity.

Furthermore, the optimisation approach adopted a machine soft start approach and reduced heating due to anticipated heat gains from manufacturing equipment at the beginning of the workday. HVAC systems also adopted a staggered 'Turn off' phase in the afternoon, reducing the power demand as machining reduced in anticipation of the end of the working day (Figure 79).

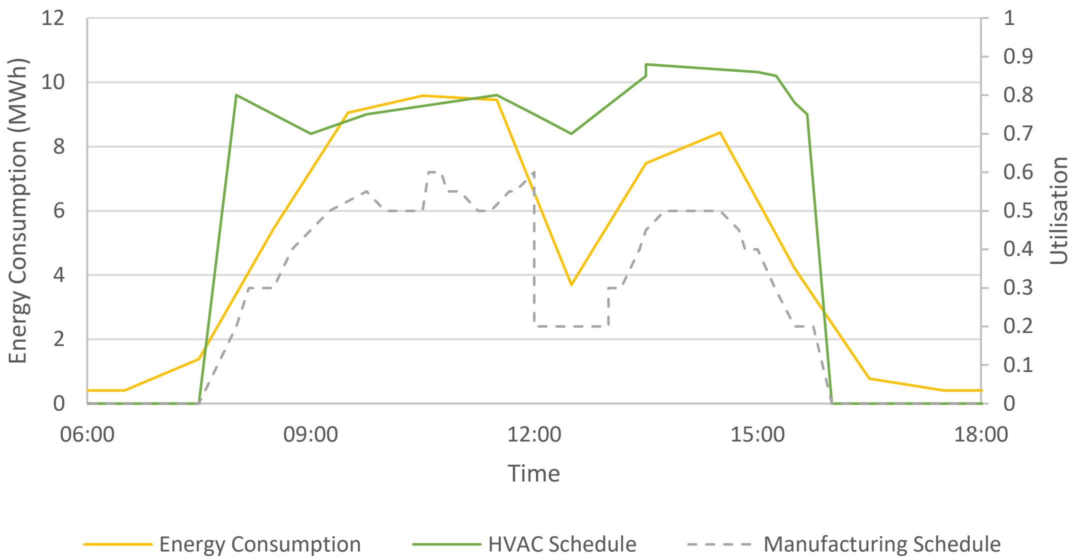



Figure 79- Optimised HVAC and manufacturing schedule for energy spike reduction

Optimising the HVAC system control alongside the manufacturing schedules not only allows for peak demand reduction, but ensures that energy is utilised in the most efficient means, through the use of scheduling based upon anticipated heat gains and manufacturing schedules. Moderating the energy consumption profile and manufacturing schedule reduces fluctuations in changes to the thermal indoor environment, thus reducing the requirements of the HVAC system to combat environmental changes. HVAC systems can also be set to be controlled based on occupant behaviour, as although manufacturing was scheduled for the course of the afternoon, HVAC controls were set with a different control regime than the rest of the day as excess waste heat in the space was less of a disadvantage than at the start of the day (provided thermal comfort conditions were still met), due to workers departing.

For the optimised system, the building energy consumption profile follows the manufacturing schedule profile more closely, with the HVAC system working alongside the manufacturing schedule. The resultant peak is lower, with a smoother total profile.

## 5.6 Prediction of Optimum HVAC Set Points- A Proactive HVAC System

Based on results displayed in Table 25 and Table 26, the best model for the MTS and MTO approach was selected for use in the development of the proactive HVAC system through HVAC set point prediction. As discussed in section 4.9, the Random Forest method outperformed others for the MTO approach, however both the ANN and Random Forest methods were utilised for the prediction of HVAC set points for the MTS environment. Results for the modified models for the prediction of HVAC set points alongside prediction of building and HVAC energy, air temperature and relative humidity are displayed in Table 27 and Table 28 for the MTO and MTS environments respectively.

Table 27- Best results for the predictive model built for the MTO environment

| **MTO** | **Prediction Error (%)** | | | | | |
|---|---|---|---|---|---|---|
| | **Building Energy** | **HVAC Energy** | **Air Temperature** | **Relative Humidity** | **Boiler Set Point** | **Chiller Set Point** |
| **Random Forest** | 3.51 | 4.44 | 4.22 | 7.63 | 0 | 4.13 |

| **MTO** | **Accuracy Metrics** | |
|---|---|---|
| | **R2** | **CV(RMSE) (%)** |
| **Random Forest** | 0.77 | 10.13 |

Similar to the results in Table 25, the ANN and Random forest models performed with similar prediction errors and similar $R^2$ values of 0.78 and 0.77 for the ANN and Random forest models respectively (Table 28).

Table 28- Best results for each predictive model built for the MTS environment

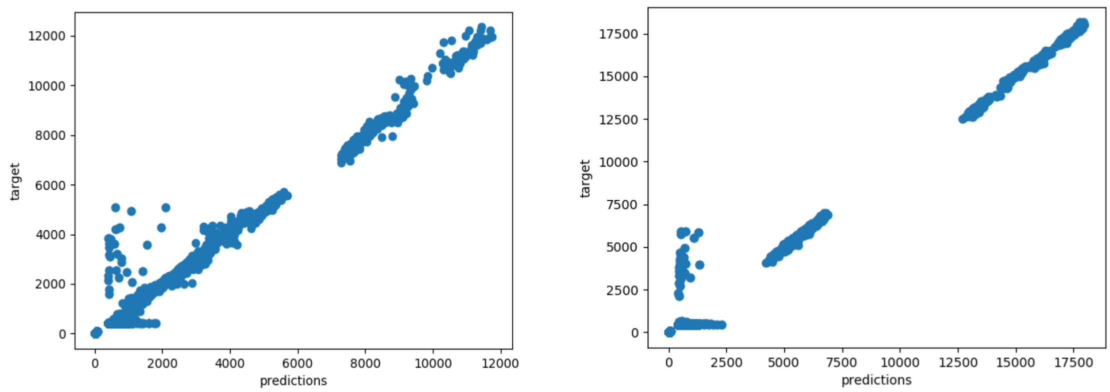
| MTS | Prediction Error (%) | | | | | |
|---|---|---|---|---|---|---|
| | Building Energy | HVAC Energy | Air Temperature | Relative Humidity | Boiler Set Point | Chiller Set Point |
| ANN | 11.65 | 12.05 | 4.34 | 6.16 | 2.78 | 3.27 |
| Random Forest | 13.9 | 14.2 | 4.35 | 7.51 | 2.79 | 2.85 |

| MTS | Accuracy Metrics | |
|---|---|---|
| | R2 | CV(RMSE) (%) |
| ANN | 0.78 | 21.7 |
| Random Forest | 0.77 | 11.2 |

The Random Forest model was selected for use in the development of the proactive system. Although the ANN outperformed the random forest model, differences in performance were minor. In the manufacturing sector, facilities may not fall into a specific MTS or MTO bracket, with some facilities obtaining characteristics of both facilities. Therefore, as the random forest model was selected for the MTO approach, it was decided that the use of the random forest model for the MTS approach would provide more consistency in methods.

Alongside the $R^2$ and CV(RMSE) metrics, the predicted variables were plotted against target variables. A high $R^2$ may be the result of a well-fitting model, but may also be the result of a model with high bias, due to model under fitting, and incorrect assumptions on the data made by the model. Therefore, alongside the $R^2$ and

CV(RMSE), the model residuals were plotted, which displays the predicted variables alongside the target (Figure 80).




MTO Environment

MTS Environment

Figure 80- Target variables vs predicted

The predicted optimum HVAC set points determined from the random forest model were fed back into a simulation model in order to determine the energy demand of the facility and conditions within the workshop with the adoption of the proactive manufacturing based HVAC system, with analytically determined optimum HVAC set points.

The aim of the manufacturing-based HVAC system was to improve the efficiency of HVAC control in order to reduce the total energy demand of the building and of the HVAC system, whilst maintaining comfortable required indoor conditions. Figure 52 displayed the energy savings based upon the adoption of the manufacturing-based HVAC system adopting the manual determination of optimum HVAC set points for a 12-month period. For such a method to be feasible and successful in practise, the discussed method for automatic and analytical determination of HVAC set points must also provide similar energy savings to that obtained through the manual approach.

Errors between the simulation conducted utilising the predicted HVAC set points and the simulation using manually determined HVAC set points for the energy demand and workshop conditions is displayed in Table 29.

Table 29- Errors in variables between predicted HVAC set points and manually determined set points for the MTS and MTO environments

| **Model** | **Prediction Error (%)** | | | |
|---|---|---|---|---|
| | **Building Energy** | **HVAC Energy** | **Air Temperature** | **Relative Humidity** |
| **MTS** | 0.61 | 1.47 | 3.85 | 7.21 |
| **MTO** | 0.66 | 1.44 | 3.86 | 7.56 |

For both the MTS and MTO models, the building energy demand of the manual and predicted HVAC set points were within less than 1 % of one another. Similarly, the error obtained for the HVAC energy was low at 1.47 and 1.44 % for the MTS and MTO environments respectively, with air temperature and relative humidity also obtaining low errors (less than 3.9 % for temperature and less than 7.6 % for relative humidity). The random forest model was therefore able to predict HVAC set points which accurately reflected the original manufacturing-based HVAC system which utilised manually obtained HVAC set points. Thus, the predictive approach was able to provide an automatic analytical approach to optimum HVAC set point determination.

Table 30 displays the energy savings obtained through the use of predicted HVAC set points for a proactive manufacturing-based HVAC system in comparison to the traditional reactive thermal comfort based HVAC system for a one month period. For comparison, results from Figure 52, Figure 53, Figure 56 and Figure 57 were broken down to provide savings between the manual approach to the manufacturing based HVAC system and traditional thermal comfort controlled HVAC for the same month and displayed alongside savings obtained through the predictive approach.

Table 30- Energy savings obtained by adopting the manufacturing based HVAC control (MFC) vs thermal comfort control (TCC) for the MTS and MTO environments, utilising predictive techniques and manual for set point determination

| **Model** | **Energy Savings (%)** | | | |
|---|---|---|---|---|
| | **Predicted MFC vs TCC** | | **Manual MFC vs TCC** | |
| | **Building Energy** | **HVAC Energy** | **Building Energy** | **HVAC Energy** |
| **MTS** | 4.96 | 11.1 | 4.37 | 9.79 |
| **MTO** | 8.90 | 17.8 | 9.49 | 19.0 |

The use of predicted set points provided similar energy savings to the manually obtained set points in comparison to the traditional thermal comfort based HVAC system. For the MTS environment, predicted set points provided greater building and HVAC energy savings, a difference of 0.59 and 1.31 % saving respectively. However for the MTO environment, manually obtained set points provided greater building and HVAC energy savings, a difference of 0.59 and 1.20 % saving respectively. Such differences in savings are minor, and each method resulted in a reduction in both building and HVAC energy demand over the traditional reactive based HVAC system. The analytical method however, stands out as the most appropriate method for determination of optimum HVAC set points to achieve energy savings due to the ease of method, and time saved in comparison to the manual approach.

Figure 81 and Figure 82 display the results for building energy demand, HVAC energy demand, air temperature and relative humidity of the MTS and MTO environments respectively, for an environment with a HVAC system controlled based on thermal comfort, manual manufacturing based control and predicted manufacturing based control.

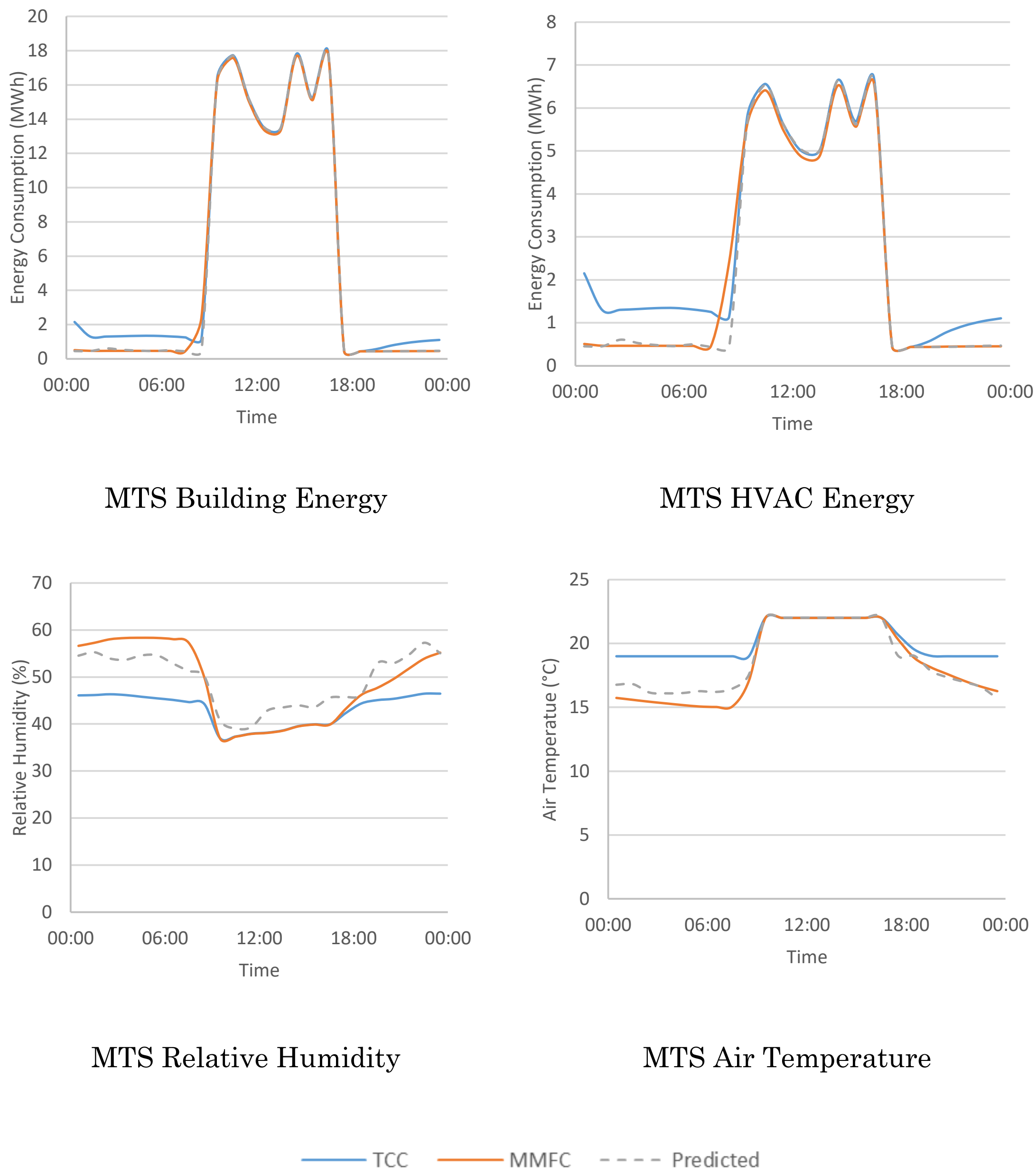
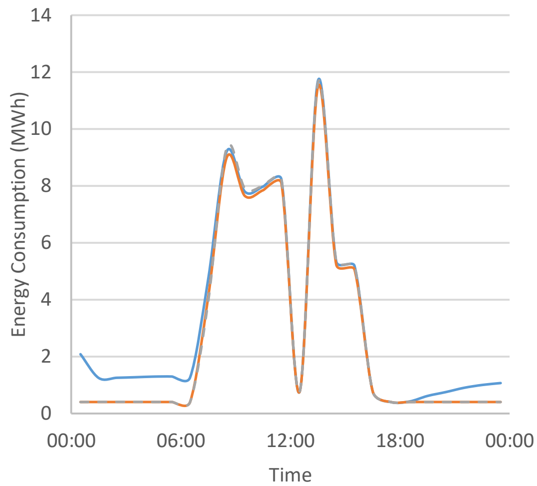
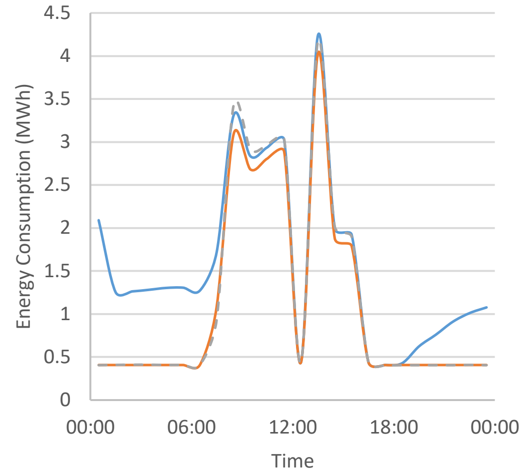


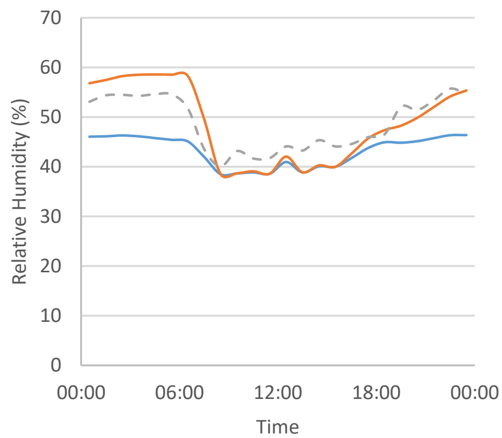

Figure 81- Results for thermal comfort controlled HVAC system (TCC), manual manufacturing controlled HVAC (MMFC) and predicted manufacturing controlled HVAC system for the MTS environment



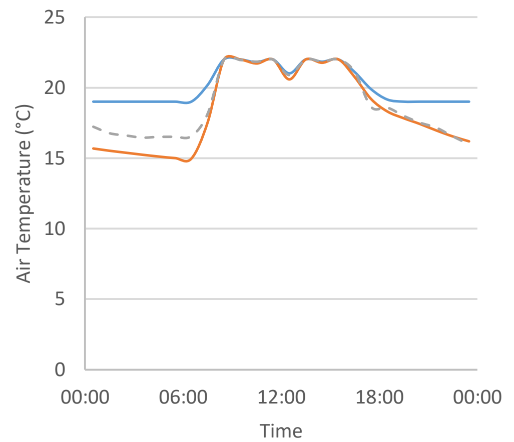

MTO Building Energy




MTO HVAC Energy




MTO Relative Humidity




MTO Air Temperature

TCC MMFC Predicted

Figure 82- Results for thermal comfort controlled HVAC system (TCC), manual manufacturing controlled HVAC (MMFC) and predicted manufacturing controlled HVAC system for the MTO environment

For the MTS and MTO environment, for both building and HVAC energy, the predicted set point method followed that of the manual manufacturing-controlled method, both obtaining a reduction in total energy demand.

However for relative humidity for both the MTS and MTO environment, the predicted approach was found to obtain values between the manual manufacturing approach and thermal comfort approach in the morning, however obtained a higher relative humidity when the machining working day begun. However these values were still in the thresholds required to ensure a comfortable working environment. Similarly, all approaches for the MTS and MTO environments provided comfortable working air temperatures.

## 5.7 Summary

The proactive approach to HVAC control provided energy savings for both the MTO and MTS facilities, with greater energy savings obtained in winter months.

For analytical determination of optimum HVAC set points and prediction of peak energy demand, linear regression provides a simplistic approach, both in model development and in the predictive capabilities. In contrast, the artificial neural network and random forest model provided the most capable models with the highest accuracy, however the deep neural networks were suggested to be utilised only for detection of patterns in the data.

The random forest model was selected as the most effective model for the prediction of energy consumption, indoor temperature and humidity, and prediction of optimum HVAC set points. Such a selection was performed based on model performance in accordance to guidelines and ability to make accurate predictions on unseen datasets.

Following identification of peak energy demands, the optimisation of both manufacturing schedules and HVAC schedules allowed for a larger reduction in peak energy demand opposed to the optimisation of each in isolation.

# Chapter 6- Conclusion

## 6.1 Introduction

This chapter concludes the investigations discussed in this thesis. The aim of the research in section 2.8 was stated as the '*Coupling Simulation with Machine Learning for the Development of a Proactive HVAC System in the Manufacturing Sector*'. Achievement of this aim would result in a more energy efficient methodology of HVAC control, specific to the manufacturing sector. Such a methodology would provide HVAC and building level energy savings, as well as the ability to monitor energy demand resulting in the identification of energy spikes, as well as workshop environmental conditions.

## 6.2 Main Findings

The main findings from the investigations in this thesis are listed below, in accordance to the objectives set in Chapter 1.

1. A critical review of literature, found in Chapter 2 was conducted in order to identify gaps in existing research. The review covered building and manufacturing energy analysis, as well as efforts to combine the two. HVAC optimisation was discussed in manufacturing, and it was found that no work had been done at investigating HVAC control in manufacturing environments, and no studies found providing a holistic analysis of manufacturing demand alongside HVAC control and building energy. The use and proven capabilities of predictive methods in energy and manufacturing analysis was highlighted, however their use in the industrial sector was found to be limited, with no studies found utilising the random forest algorithm.

2. IES-VE allowed for the holistic analysis of both the manufacturing equipment and building facility, allowing for modelling of manufacturing equipment, their schedules and corresponding heat gain profiles, along with occupant behaviour, building fabric,

weather conditions and operation of the HVAC system. Use of one modelling tool allowed for manufacturing schedules to be analysed and optimised alongside that of the HVAC system, encompassing all relevant interacting thermal energy flows to develop a more efficient HVAC control approach. The importance of a holistic simulation analysis of both building and manufacturing energy flows has also been discussed in a peer reviewed journal paper [197].

3. Through the use of the Spearman rank correlation coefficient, there was found to be negligible relationship between the building and HVAC energy demand and degree-days for a manufacturing environment. In contrast, a high correlation was found between building and HVAC energy demand and manufacturing demand. This was further confirmed with the simulation of a manufacturing environment with equipment, displaying negligible seasonal variation in energy demand, in contrast to the facility with no equipment, showing significant seasonal variations in energy demand. It was concluded that although climate had an impact on energy consumption of the building, degree days cannot be used as an indicator of consumption trends or predictions, and thus for building energy analysis in the industrial sector. This result has also been published in a peer reviewed journal paper [191].

4. Through the use of simulation and knowledge regarding the interaction between building energy consumption, outdoor weather conditions and manufacturing demand, a proactive manufacturing based HVAC control system was developed, where optimum HVAC controls were set in advance, and utilised concepts of heat recovery from manufacturing equipment. Such an approach resulted in HVAC energy savings of 16.3 % for the MTS manufacturing production environment and 26.9 % from the MTO environment. Furthermore, a total energy saving of 7.61 % for a MTS environment, and 14.1 % for an MTO environment was obtained.

5. LSMLR, ANN, DNN and random forests were analysed for suitability towards the analytical determination of optimum HVAC set points. Random forest achieved the highest accuracy for the prediction of building and HVAC energy, workshop air temperature and relative humidity, along with optimum HVAC set points, with ANNs also obtaining a high accuracy. The prediction of optimum set points removes the need for time-consuming manual control of the HVAC system, and allows HVAC systems to be controlled proactively, prior to any significant changes to indoor conditions. Furthermore, the prediction of workshop air temperature and humidity provides a means of condition monitoring, to ensure the facility maintains a comfortable working temperature for occupants, as well as optimum conditions for product quality if required. The prediction of building energy consumption and indoor conditions was performed in a published journal paper, [191], utilising deep machine learning techniques, further emphasising the potential of predictive machine learning models in the manufacturing and energy sector.

6. Through the use of a random forest model, upcoming spikes in overall building energy demand were identified. The use of synchronous optimisation of both manufacturing schedules and HVAC controls allowed for a 15.1 % reduction in peak energy demand over the course of a working day. The use of predictive models allowed spikes in energy demand to be identified, coupled with simulation for the subsequent optimisation of schedules prior to implementation into a real world environment. Such a result provides a high incentive for manufacturing companies to adopt energy efficiency improvement strategies due to financial savings.

7. Combining the simulation and predictive approaches in this study, a framework for the development of a proactive based manufacturing HVAC system can be determined. A simulation model of a manufacturing environment can be utilised to gather training data for the subsequent development of predictive models. Such predictive models can be utilised to predict spikes in building energy demand, HVAC demand, along with optimum HVAC set points, and resulting air temperatures and

humidity. Through continuous data capture, the predictive models can be continuously trained upon new data, for continuous model improvement.

## 6.3 Contribution to Knowledge

Highlighted in Chapter 2, a number of gaps were identified in the field of building energy analysis in the industrial sector. Through the work conducted in this thesis, the following contributions to knowledge were made.

1. Through the use of a singular simulation tool, a holistic analysis of a manufacturing facility was conducted. The relationship between manufacturing demand and building energy and HVAC energy demand were identified. with the suspicions behind suitability of the degree day method in manufacturing confirmed as unsuitable.

2. The concept of a proactive manufacturing based HVAC control system was introduced, of which achieved energy savings of 7.61 and 14.1 % for a MTS and MTO manufacturing environment respectively.

3. The use of machine learning confirmed the suitability of predictive methods for energy analysis in the manufacturing sector, and allowed for the determination of optimum HVAC set points in development of the proactive manufacturing based system. The adoption of the random forest algorithm was successfully applied to manufacturing environments.

4. Optimisation of HVAC control as well as manufacturing schedules provided a means of reducing spikes in energy consumption as well as total energy consumption, of which can be achieved through predictive modelling.

5. As a result of this thesis, 4 peer reviewed journal papers have been published, [191], [197]–[199], along with the presentation of 2 papers at an international and national conference.

## 6.4 Further Work

The research presented in this thesis provides a foundation of key findings and framework for further research and development, of which is listed below.

1. The accumulation of more training data for predictive models, specifically real data from a manufacturing environment, regarding machine schedules, energy consumption, occupancy data and climatic data would allow models to improve prediction accuracy as well as learn from stochastic events such as machine breakdown, occupancy fluctuations and unpredictable climatic events.

2. Applying the methodology to additional case study environments, and facilities of varying size, environmental condition requirements and manufacturing demand would highlight any need for methodology adjustments or supplementary requirements for certain facility types.

3. The implementation of the proactive system into a manufacturing facility alongside real time data capture would allow for continuous predictive model training and constant model learning to provide continuous improvements in the predictive of optimum HVAC set points.

4. The implementation of a feedback loop would be beneficial, allowing for the specification of whether predicted optimum HVAC set points provided a suitable level of thermal comfort within the manufacturing environment, of which can be used to alter HVAC set points accordingly.

5. Prior to implementation into a real manufacturing environment, the ability to accurately and quantitatively model heat gain profiles from manufacturing

equipment into the surrounding space should be performed and imported into the simulation model in order to determine the impact of specific manufacturing equipment on the HVAC requirements of the space.

6. The development of a 'Black Box' software tool would allow the methodologies developed in this thesis to be distributed and allow companies worldwide to acquire the benefits of an intelligent HVAC system. Such a tool would provide the knowledge required for SMEs to obtain quantifiable measures of energy consumption.

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# Appendix

## Appendix A

Case Study data set

Displayed in Appendix A.1 is the data collected from 13 studies which analysed the energy consumption in manufacturing facilities.

Appendix A.1 – Data utilised to build a dataset for the generalised case study

| Study | Location | Total building energy consumption | HVAC energy consumption | Manufacturing energy consumption | Machine Schedule | Facility operation | Total Area ($m^2$) | Room Conditions | Occupancy | Misc |
|---|---|---|---|---|---|---|---|---|---|---|
| Oates, [102] | London | 105.8 MWh/ yr | - | 78.46 Mwh/yr | M-F, 09:00-17:00 | M-F, 09:00-17:00 | | 18 °C | | Walls; concrete, 0.2m thick, density - 2400kg/m3, thermal conductivity- 1.5w/m.K, heat capacity- 800 J/kg.K, absorptivity- 0.65, emissivity- 0.9. roof;0.01m steel. |
| Weeber, [88] | Germany | 205 MWh/ yr | - | - | M-F | M-F | | 22 °C, 20% relative humidity | | internal machine heat gains- 100-200W/m2 or 15-20% of machine load |
| Alvandi, [96] | - | 2635.4 4 MWh/ yr | | 4.59- 9.24 kWh/piece | | | | | | |
| Dababneh, [109] | Chicago | | | | M-F, 9:00-17:00. 32 15min intervals, 13 before 12:00, 19 after 12:00 | | 400 | 18-22 °C | | Peak energy demand; 89.9-94 kW.<br>5 machines, 4 buffers, 320 parts made per day. |

(Continued)

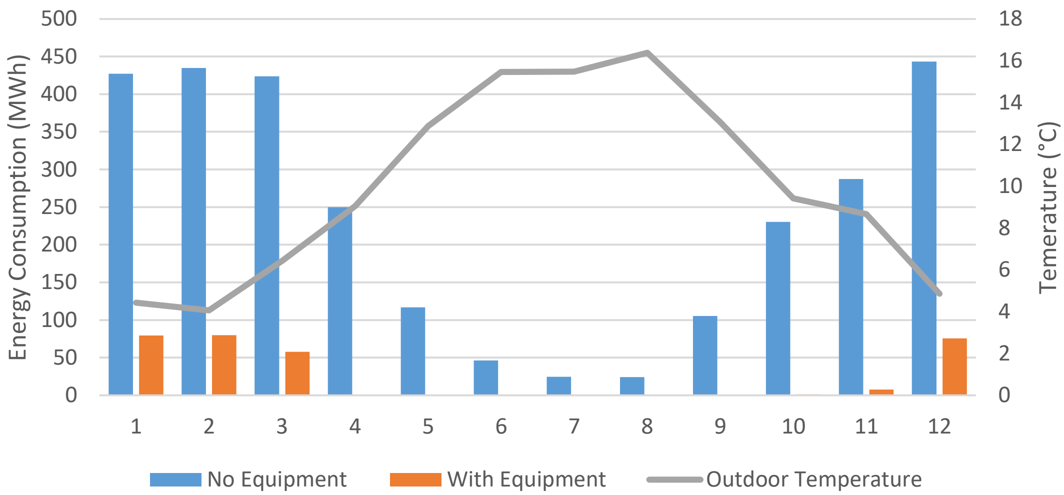
| Study | Location | Total building energy consumption | HVAC energy consumption | Manufacturing energy consumption | Machine Schedule | Facility operation | Total Area ($m^2$) | Room Conditions | Occupancy | Misc |
|---|---|---|---|---|---|---|---|---|---|---|
| Wilson, [163] | - | - | - | 2594 Mwh/yr. 9.9 kwh/ piece | 235972 pieces/yr, | | | | | |
| Kannan, [160] | - | 800 MWh | 15% of total energy | 680 Mwh/yr | | 4575hr/ y, 8hr shifts | 950 | | | |
| Herrmann, [93] | Germany | 17.285 MWh / month | | | 1part/min, 366hrs/month | | | | | |
| Wright, [34] | London | 195 Mwh/yr | | 43.2 MWh/yr | M-F, 09:00-17:00 | | | | | |
| Johansson, [71] | - | - | - | 3121.72 Mwh/yr, 85.4 kwh /piece | | | | | | |

(Continued)

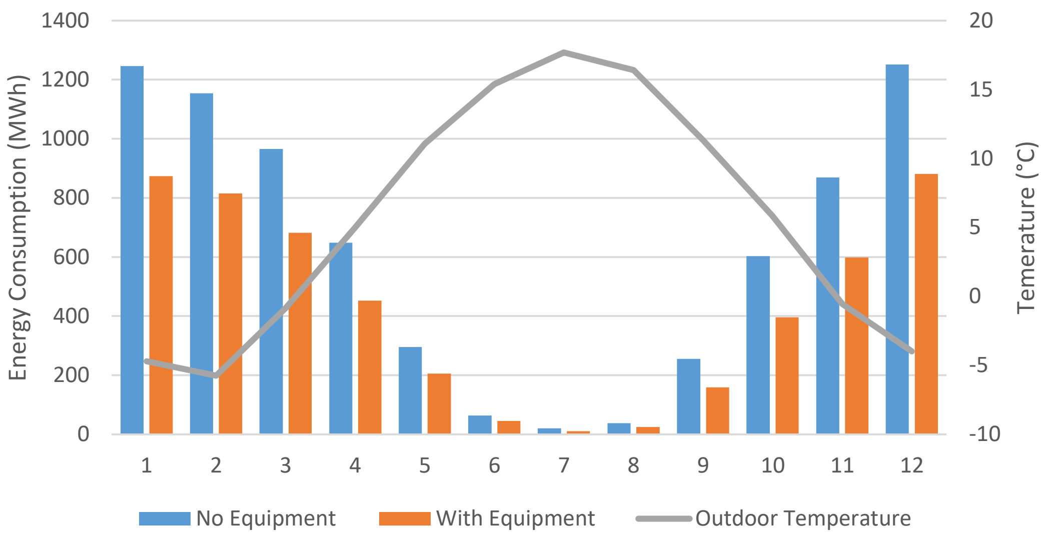
| Study | Location | Total building energy consumption | HVAC energy consumption | Manufacturing energy consumption | Machine Schedule | Facility operation | Total Area ($m^2$) | Room Conditions | Occupancy | Misc |
|---|---|---|---|---|---|---|---|---|---|---|
| Bleicher, [98] | | 8000 Mwh/yr | | | | | 15000 office area, 20500 production area | | 500 | 45 machines (32 machine tools, 8 ovens and 5 laser) |
| Fromme, [161] | Russia | 97643 MWh/yr | 47708 Mwh/yr | 27600 Mwh/yr | 09:00-10:00, 16:00-19:00 | 09:00-10:00, 16:00-19:00 | 120,000 | | 4000 | trailer production site, low level of automation so expected lower energy |
| Katunsky, [87] | | | 492.88MWh/yr | 20 machines (400W each), | | | 648- one manufacturing room | | 20 | Machine heat gains 12.45W/$m^2$, 4.5W/$m^2$ internal gains from lighting, 4000W internal gains from people |
| Moynihan, [162] | | | boiler consumption 88191 MMBtu/yr | 1.64MW | M-F, 08:00-17:00 | M-F, 08:00-17:00, reduced HVAC outside these hrs | 16722 | 18.3-21.1 °C | 0.0336 person/sqm | Machine internal gains 60W/$m^2$ 1 boiler (CB700-100CleaverBrooks), 4ovens (1.6MMBtu/hr), 2 compressors (air)(300hp and 200hp Quincy and Sullair), 5 ammonia compressors. |

# Appendix B

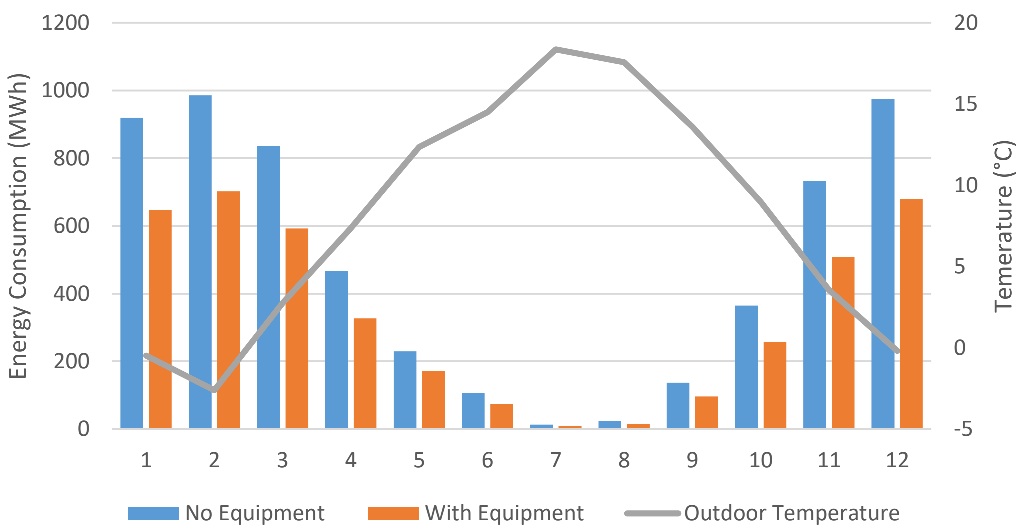
Displayed in Appendix B.1- B.4 is the boiler energy profile for each of the analysed locations, over a period of 12 months, for a manufacturing environment with and without equipment.



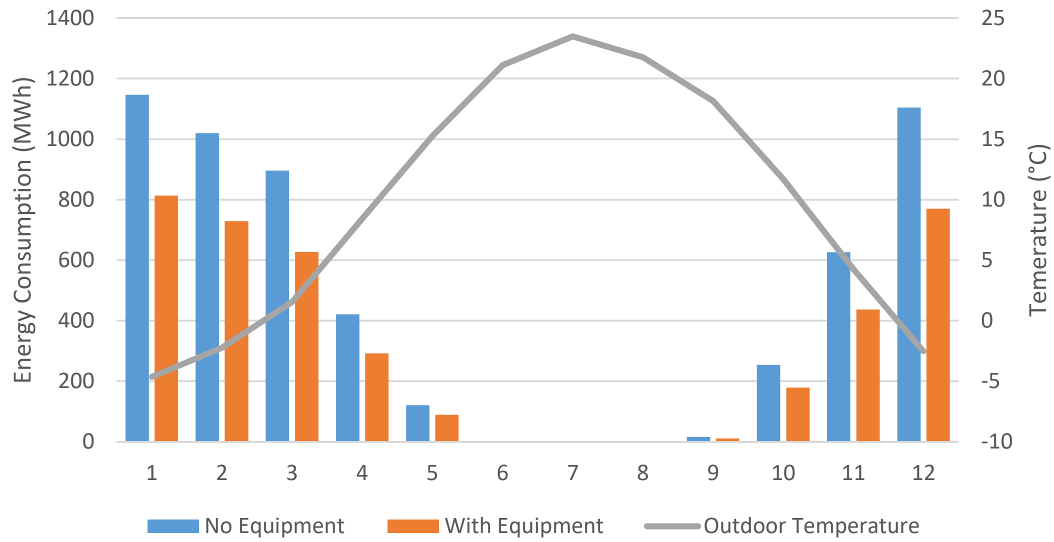

Appendix B.1- Boiler energy consumption and outdoor air temperature for a facility in London, with and without equipment




Appendix B.2 - Boiler energy consumption and outdoor air temperature for a facility in Russia, with and without equipment

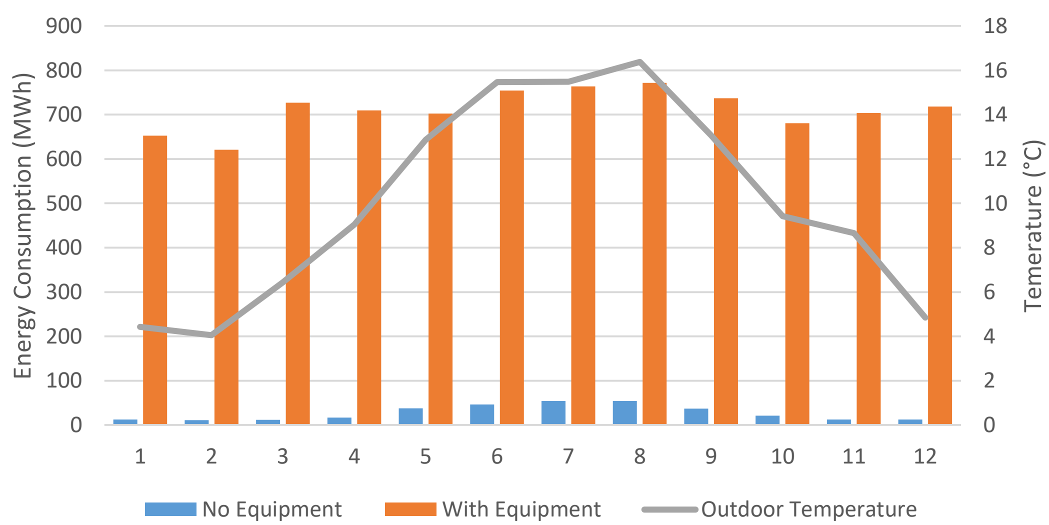



Appendix B.3 - Boiler energy consumption and outdoor air temperature for a facility in Germany, with and without equipment

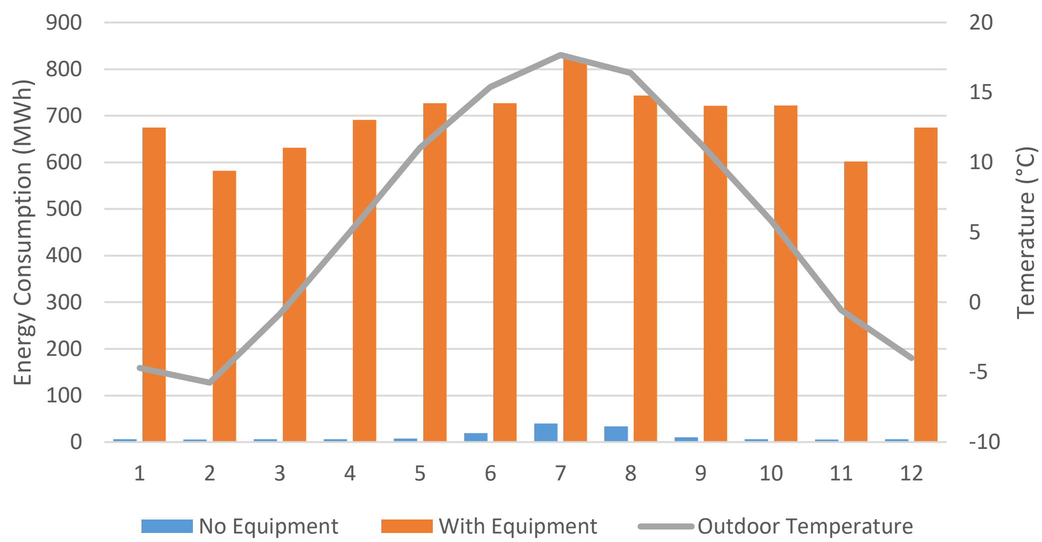



Appendix B.4 - Boiler energy consumption and outdoor air temperature for a facility in Chicago, with and without equipment

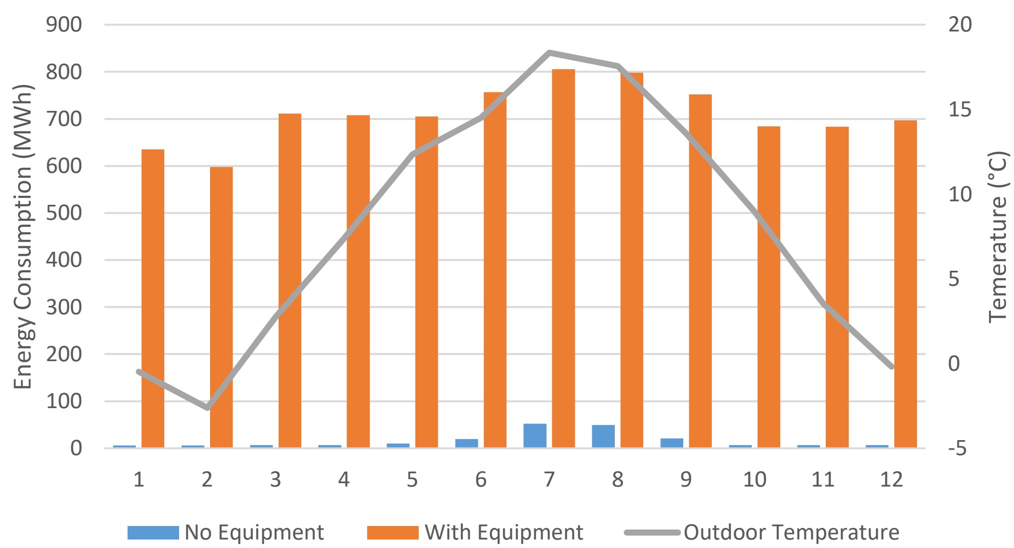
Displayed in Appendix B.5- B.8 is the chiller energy profile for each of the analysed locations, over a period of 12 months, for a manufacturing environment with and without equipment.



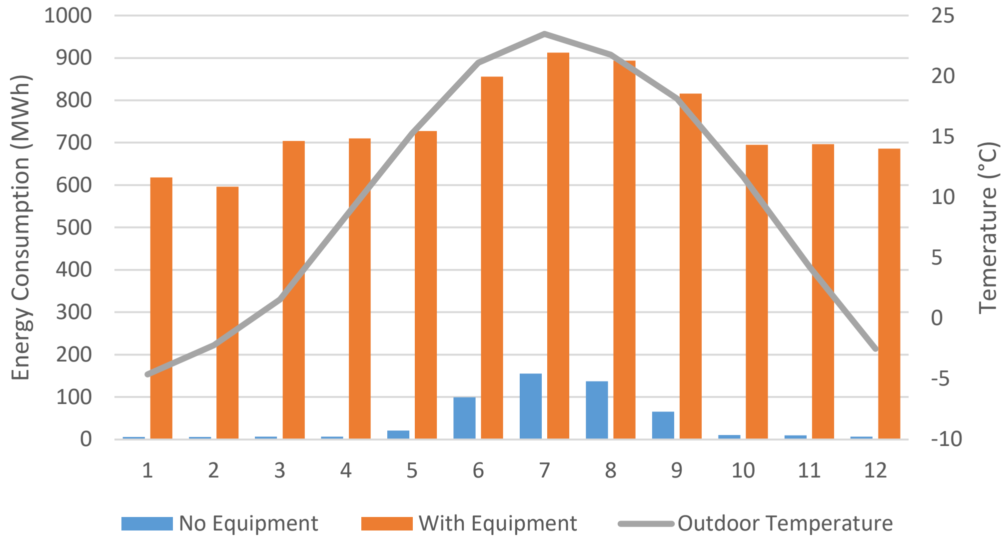

Appendix B.5 - Chiller energy consumption and outdoor air temperature for a facility in London, with and without equipment




Appendix B.6 - Chiller energy consumption and outdoor air temperature for a facility in Russia, with and without equipment




Appendix B.7 - Chiller energy consumption and outdoor air temperature for a facility in Russia, with and without equipment




Appendix B.8 - Chiller energy consumption and outdoor air temperature for a facility in Chicago, with and without equipment

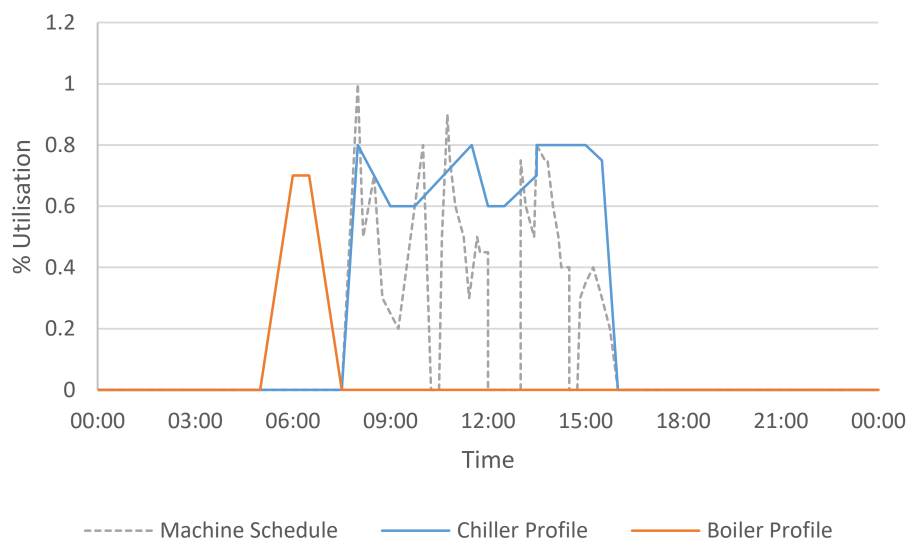
# Appendix C

## HVAC Schedules, MTO environment

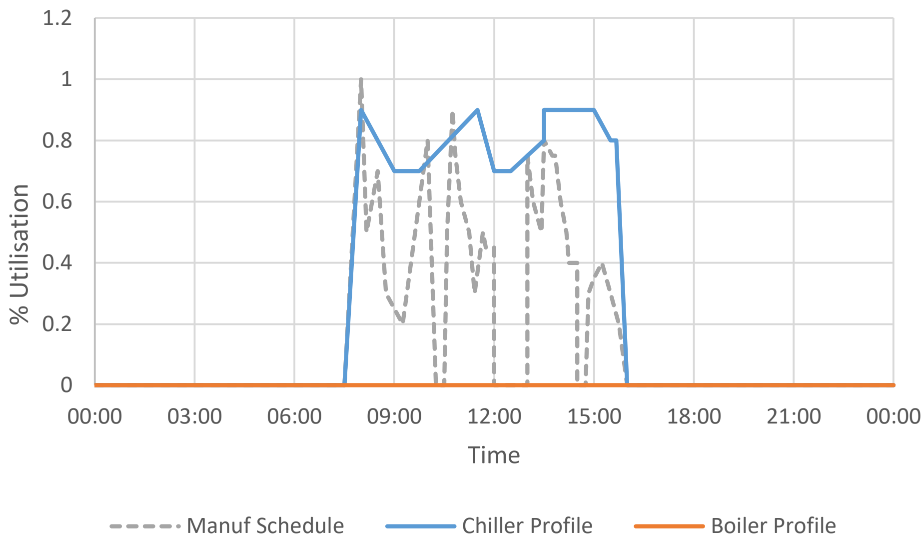
For the MTS environment, manufacturing schedules were consistent throughout the year and on a daily basis. Boiler systems were turned off from June-September, however in the months October-May, adopted the schedule seen in Figure 40. Chiller systems were utilised yearly, again adopting the regime seen in Figure 38.

For the MTO environment, manufacturing schedules saw greater fluctuations, and therefore HVAC schedules adopted a larger seasonal variation.

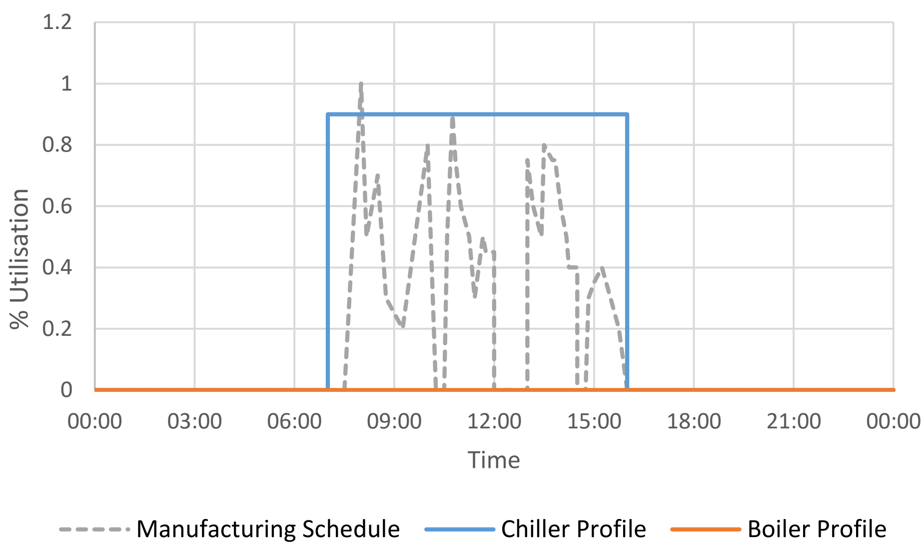
Displayed below in Figures C.1-C.5 are sample HVAC and manufacturing schedules for the MTO environment for each month of the year.



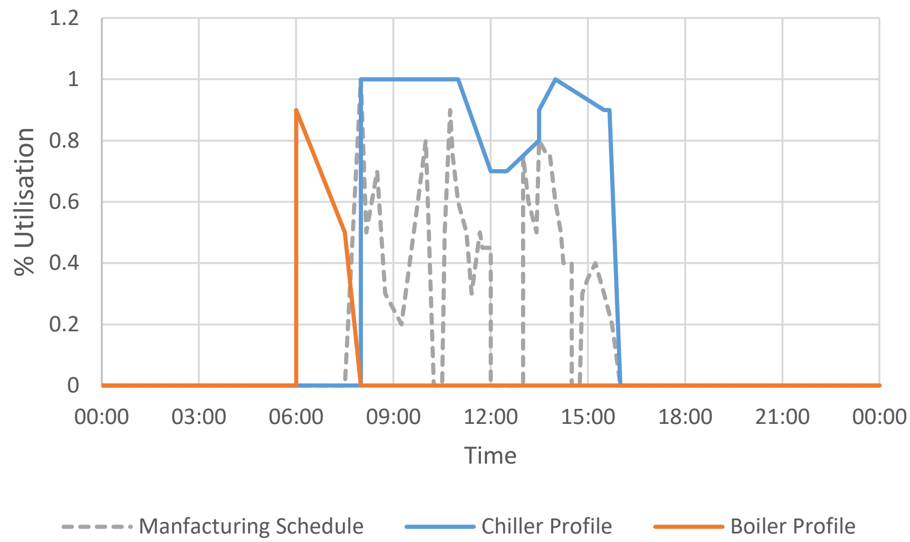

Appendix C.1- Manufacturing, boiler and chiller schedule for January and February



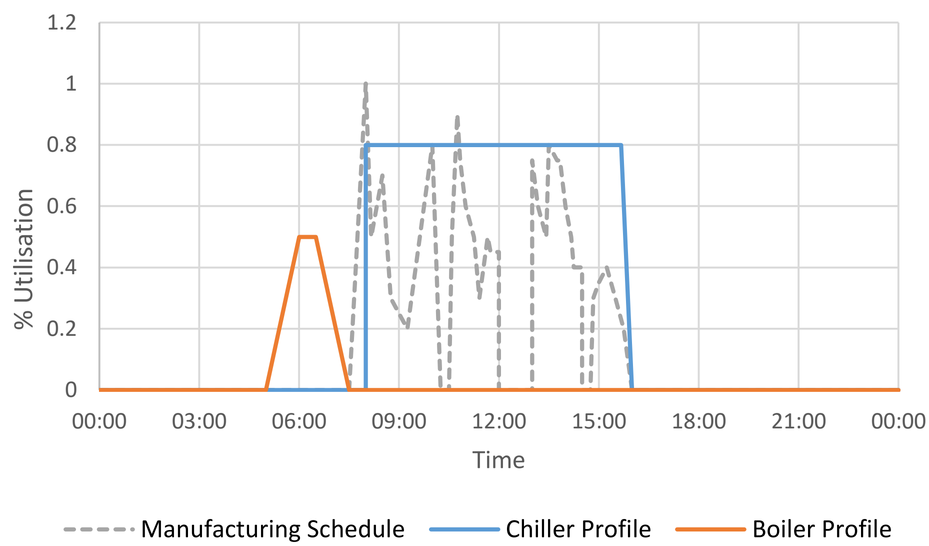

Appendix C.2- Manufacturing, boiler and chiller schedule for  March, April and May




Appendix C.3- Manufacturing, boiler and chiller schedule for June, July and August



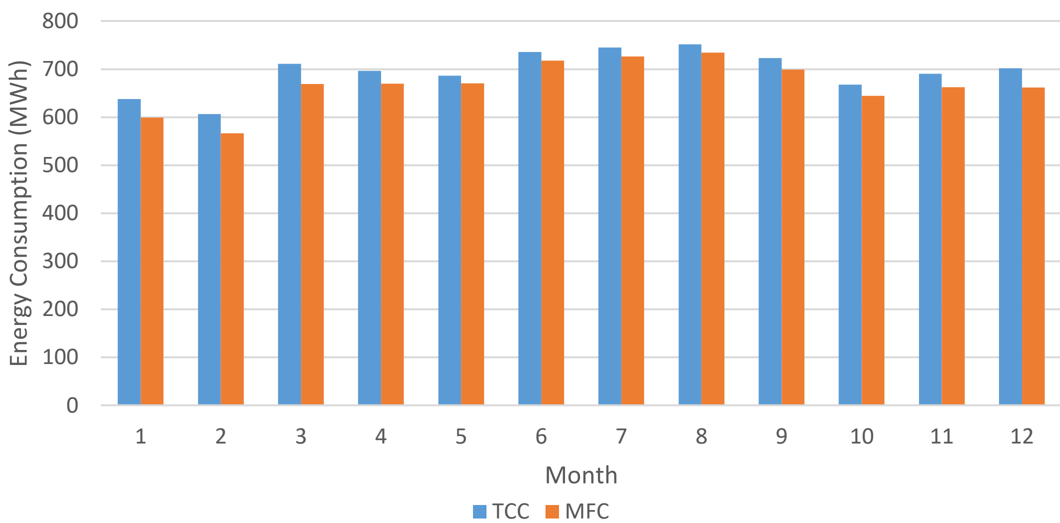

Appendix C.4- Manufacturing, boiler and chiller schedule for September and October



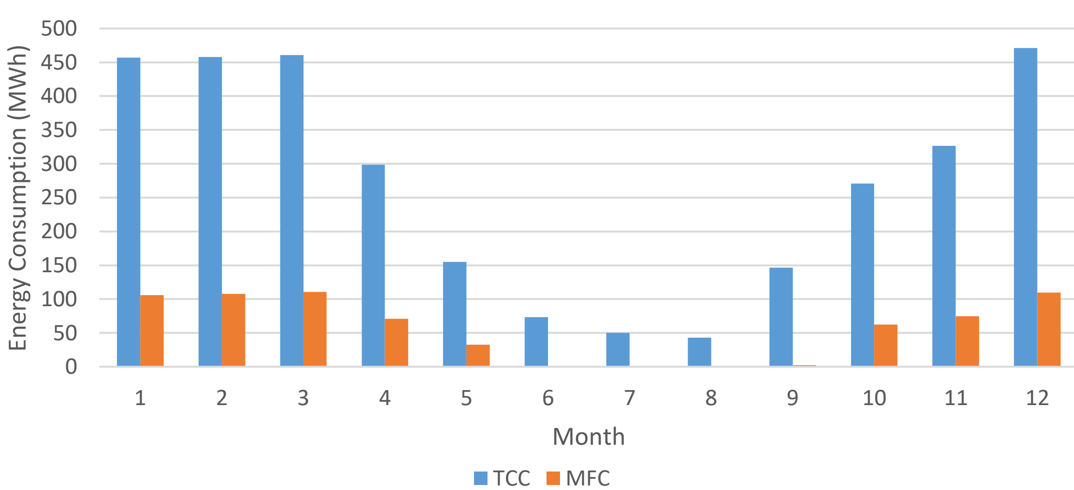

Appendix C.5- Manufacturing, boiler and chiller schedule for November and December

# Appendix D

Appendix D.1 and D.2 display chiller and boiler energy consumption profiles for the MFC and TCC control HVAC system over a period of 12-months for the MTS environment respectively.



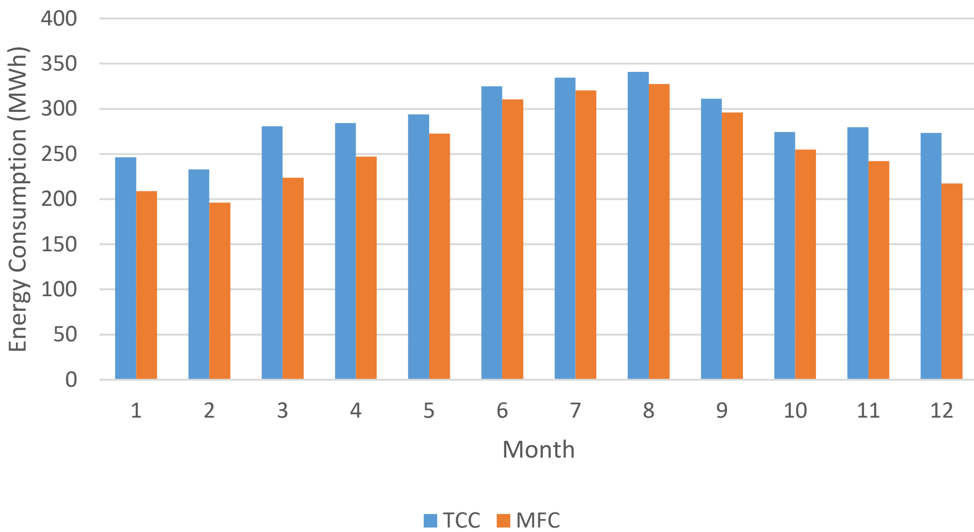

Appendix D.1 - Chiller energy consumption over a 12-month period for the MTS environment



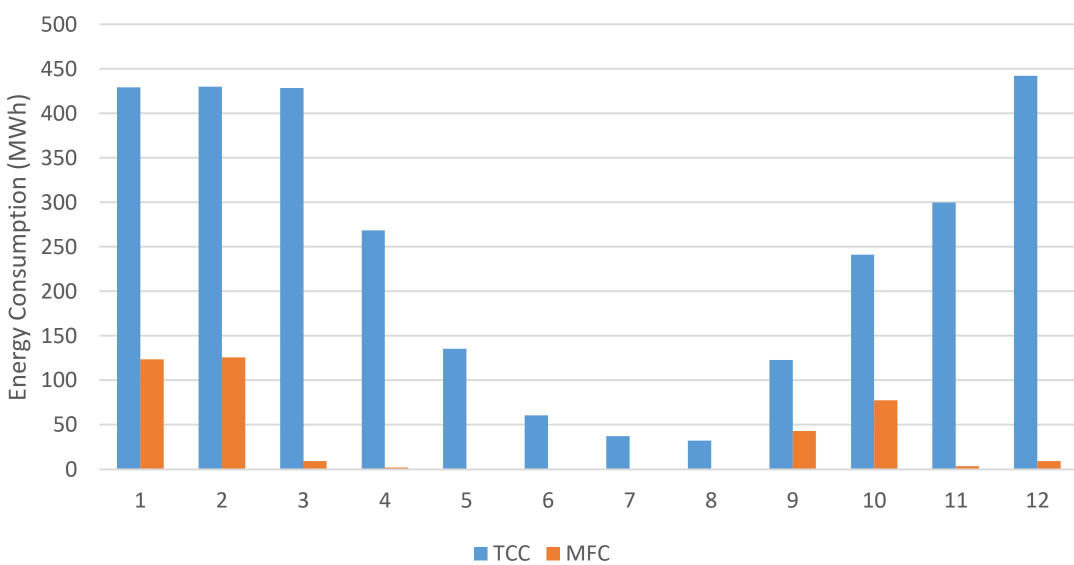

Appendix D.2 - Boiler energy consumption over a 12-month period for the MTS environment

# Appendix E

Appendix E.1 and E.2 display chiller and boiler energy consumption profiles for the MFC and TCC control HVAC system over a period of 12-months for the MTO environment respectively




Appendix E.1 - Chiller energy consumption over a 12-month period for the MTO environment




Appendix E.2 - Boiler energy consumption over a 12-month period for the MTO environment