Real-Time and Semantic Energy Management Across Buildings in a District Configuration

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Declaration

This work has not been submitted in substance for any other degree or award at this or any other university or place of learning, nor is being submitted concurrently in candidature for any degree or other award.

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Abstract

Existing building and district energy management strategies are in urgent need of an overhaul to meet the energy and environmental challenges of the 21st Century. The immense growth in the availability of data through the Internet of Things (IoT), the decentralisation of energy generation, and the increasing power of Artificial Intelligence (AI) presents an opportunity to achieve a paradigm shift in the way energy is controlled and managed.

To contribute to this field, this PhD project undertook a thorough literature review combined with a participatory, action research approach to identify and understand the key challenges faced by facility managers and to identify potential areas of improvement. Following this, the PhD thesis aims to tackle three key research areas using simulated case study experiments. These aim to optimise thermal energy management within buildings at a zone-level, control energy generation at a district-level, and combine the learnings from these two experiments with a holistic energy management solution that controls both the energy supply and demand at a building and district-level.

At a building-level, a model predictive control approach combining a genetic algorithm and surrogate artificial neural network is used. A predictive and context aware controller is able to produce 24 hour heating set point schedules for each zone within a building. This approach achieved an energy saving of 18% whilst maintaining thermal comfort for users. The methodology also had the capability to adapt to dynamic energy pricing tariffs and capable of optimising for energy cost by shifting load to cheaper periods.

At a district-level, a predictive, optimisation-based approach was developed to determine the operation of a multi-vector, district heating, energy centre. When thermal storage and several generation sources are available, alongside variable renewable energy generation and building demand, static, rule-based controllers cannot perform adequately in all conditions. Instead, the optimisation-based approach, developed in this thesis, was able to increase profit to the energy centre by 45% as well as decrease CO_2 emissions whist adapting to errors in energy demand and supply forecasting.

Finally, the most significant contribution of this thesis was provided by ef-

fectively combining the approaches made at a building and district-level. This case study aimed to simultaneously control the energy generation of the district energy centre, alongside the thermal demand of one of the buildings within the district. The additional flexibility provided by partially controlling the building demand led to a further 8% increase in profit to the energy centre, compared to just optimising energy supply. This demonstrates the vital importance of treating the consumer as an integral, active component of the energy system.

It is argued that the contributions made throughout this thesis will become more relevant when coupled with additional research fields. This includes the growth in available data from IoT sources, advanced AI including unsupervised learning, and utilising a shared semantic description of smart building, smart energy and smart city concepts. At its core, this thesis aims to demonstrate that 'thinking', predictive, control strategies, that are more context-aware, can achieve significant benefits over the traditional reactive, rule-based controllers of the past.

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Nomenclature

Variables

C	Capacity of controllable generation
CO_2	CO_2 produced
c_p	Specific heat capacity of water
E	Electrical energy
F	Primary fuel consumption
f	Net cost (fitness)
I	Income
L	Load percentage of controllable generation
m	Mass
P	Tariff price of fuel
Q	Heat generated
$\dot{Q}$	Heat demand
$Rel\eta$	Relative efficiency of controllable generation units
S	Load percentage of thermal storage
T	Temperature
V	Cost of primary fuel
X	CO_2 conversion ratio
η	Nominal efficiency of controllable generation units

Subscripts

el	Electrical
t	Timestep
th	Thermal

Superscripts

$Apar$	Apartment Building
CHP	Combined Heat and Power
FIT	Feed in Tariff
GB	Gas Boiler

$Hosp$	Hospital building
Hot	Hotel Building
HP	Heat Pump
i	Indoor Temperature
PV	Solar Photovoltaics
RHI	Renewable Heat Incentive
S	Thermal Storage
Sch	School Building
sp	Set Point Temperature
U	Generation Unit

Abbreviations

AHU	Air Handling Unit
AI	Artificial Intelligence
$ANFIS$	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ARX	Auto-Regressive model with eXogenous inputs
$BCVTB$	Building Controls Virtual Test Bed
$BEMS$	Building Energy Management Systems
BIM	Building Information Modelling
BMS	Building Management System
BRP	Balance Responsible Party
CFD	Computational Fluid Dynamics
CHP	Combined Heat and Power
COP	Coefficient of Performance
CV	Coefficient of Variation
DHC	District Heating and Cooling
DNN	Deep Neural Network
DSO	Distribution System Operator
$ESCo$	Energy Service Company
FIT	Feed in Tariff
GA	Genetic Algorithm
$GSHP$	Ground Source Heat Pump
$HEMS$	Home Energy Management System
HP	Heat Pump
HPC	High Performance Computing
$HVAC$	Heating Ventilation and Air Conditioning
IoT	Internet of Things
KPI	Key Performance Indicators

$LSTM$	Long Short-Term Memory
$MAPE$	Mean Absolute Percentage Error
MAS	Multi-Agent System
MBE	Mean Bias Error
$MILP$	Mixed-Integer Linear Programming
$MINLP$	Mixed-Integer Non-Linear Programming
MLP	Multi-Layer Perceptron
MPC	Model Predictive Control
$NNARX$	Neural Network Auto-Regressive model with eXogenous inputs
$P2G$	Power to Gas
PID	Proportional Integral Derivative
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
PSO	Particle Swarm Optimisation
PV	Photovoltaic
RC	Resistor Capacitance
RHI	Renewable Heat Incentive
$RMSE$	Root Mean Squared Error
$SCADA$	Supervisory Control and Data Acquisition
SSE	Sum of Squared Error
SVM	Support Vector Machine
ToU	Time of Use
TSO	Transmission System Operator
$V2G$	Vehicle to Grid

List of Publications

Journal Publications

Jonathan Reynolds, Muhammad Waseem Ahmad, Yacine Rezgui, and Jean-Laurent Hippolyte. Operational supply and demand optimisation of a multi-vector district energy system using artificial neural networks and a genetic algorithm. *Applied Energy*, 235:699–713, 2019

Jonathan Reynolds, Yacine Rezgui, Alan Kwan, and Solène Piriou. A zone-level, building energy optimisation combining an artificial neural network, a genetic algorithm, and model predictive control. *Energy*, 151:729–739, 2018

Jonathan Reynolds, Muhammad Waseem Ahmad, and Yacine Rezgui. Holistic modelling techniques for the operational optimisation of multi-vector energy systems. *Energy and Buildings*, 169:397-416, 2018

Jonathan Reynolds, Yacine Rezgui, and Jean-Laurent Hippolyte. Upscaling energy control from building to districts: Current limitations and future perspectives. *Sustainable cities and society*, 35:816–829, 2017

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1 | Introduction

Our energy transition towards a cleaner, more efficient, and renewable future, is a process of paramount importance. This research aims to produce practical methods to smooth the transition and produce new energy management solutions to adapt to this energy landscape. This Chapter will outline the core challenges and drivers from an energy, environmental and technological perspective. It will also define the central hypothesis and subsequent research questions that this thesis will address. Finally the key contributions resulting from this research are summarised and presented.

1.1 Global View

One of the greatest global challenges of this century is the requirement to transition from an energy infrastructure primarily based on fossil fuels to an affordable, sustainable, and resilient energy system that leads to a reduction in greenhouse gas emissions and mitigates the effects of climate change whilst maintaining economic growth. The first key landmark in aiming to tackle the problem of global warming was the Kyoto protocol [1] which legally committed signatories to binding targets on greenhouse gas emissions. The Kyoto Protocol was subsequently criticised for largely ignoring the emissions from developing countries as well as failing to enforce penalties for countries that failed to meet their emission targets. The initial foundation provided at Kyoto was improved upon in 2015 with the adoption of the Paris climate agreement [2]. This treaty set a global target of reducing global temperature rises to "*well below 2 °C* " with an ambition of limiting temperature rises to below 1.5°C .

Despite widescale recognition of the need to reduce greenhouse gas emissions, global energy consumption has continued to rise as demonstrated in Figure 1.1. This is partly due to population growth, increased access to electricity, and industrialisation of developing countries. The context is somewhat different within the European Union (EU) where total primary energy consumption and primary energy consumption from fossil fuels is beginning to decrease as shown in Figure 1.2. As a result of both the Kyoto Protocol and the Paris climate agreement, the EU implemented clear targets regarding the reduction of greenhouse gas emissions, increasing the share of renewable energy and the improvement of energy efficiency. These targets have been directly translated into specific targets for each member state to be delivered by 2020, 2030 and 2050 with the eventual aim of an 80% reduction in greenhouse gas emissions compared to 1990 levels in both the UK and the entire EU.

1.1.1 Renewable Energy Expansion

To achieve global emissions targets, significant effort has been placed on increasing the share of consumed energy derived from renewable resources. Renewable energy resources are those derived from naturally replenishable phenomena such as sunlight, wind, biomass, geothermal heat, tides and rain [6]. Historically, the largest form of renewable energy was produced from hydropower at either large scales, facilitated by dams, or smaller scales deployed in rivers. The renewable energy sector has now expanded to include wind turbines, solar photovoltaic (PV) panels and beyond, to novel emerging technologies such as concentrated solar power stations, tidal stream turbines, and tidal lagoons. However, there is no silver bullet with regards to renewable energy with a balance needing to be struck between opinions of locals who may perceive their presence as an eyesore or may object to land being denied as use for food production.

Within the power sector, total renewable power capacity has more than doubled in the decade from 2007 to 2017 [7], fuelled largely by expansions in solar PV and wind power capacity as shown in Figure 1.3. These renewable technologies are now comparable in price to electricity generation from fossil fuels and therefore require little to no subsidy from national governments [8]. Whilst the decarbonisation of the power sector continues to progress, decarbonisation of other sectors such as heating, cooling and transport remains a significant challenge.

1.1.2 Energy Security

As well as the environmental obligations and economic desires, energy security is another important factor in the current energy transition. Energy security can be viewed from two angles [9]; a political point of view due to reliance on foreign imports and hence lack of control over import prices, and a dispatch point of view in which energy networks need to balance short-term demand surges to prevent black-outs or voltage drops.

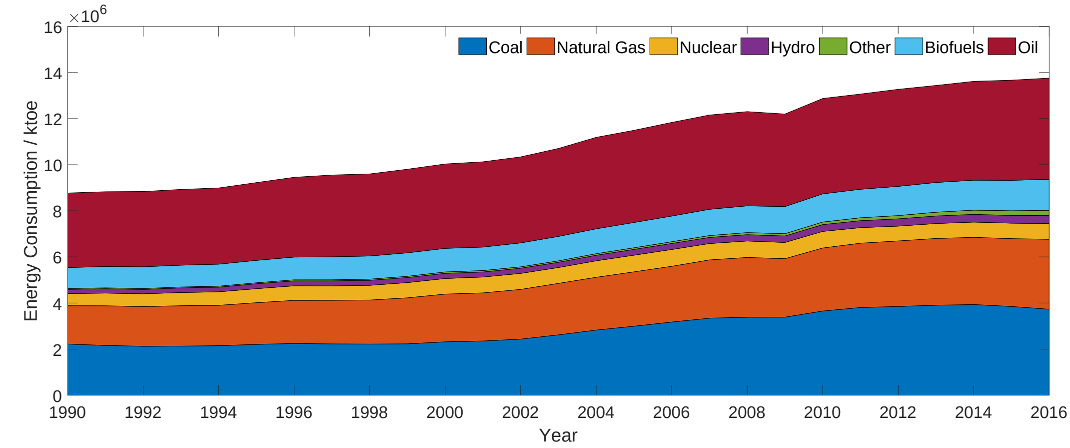


Figure 1.1: Global energy consumption by fuel source, Data from: [3]

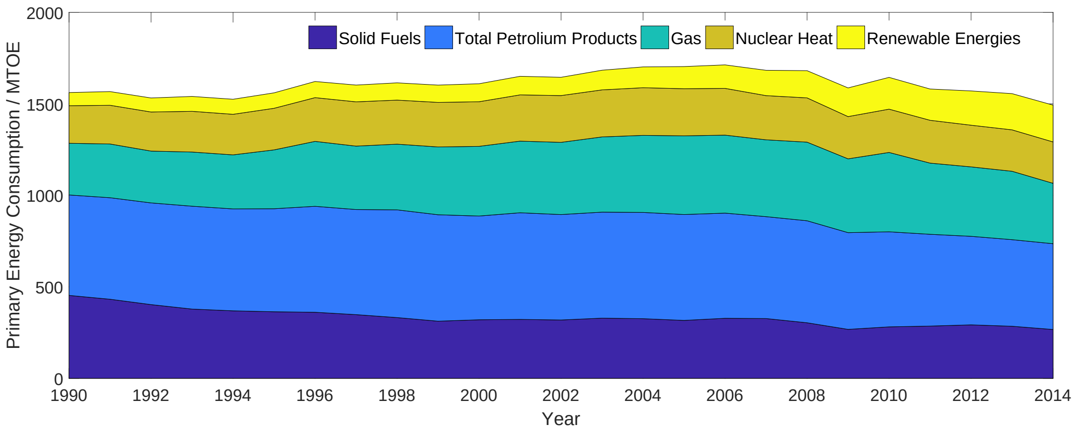


Figure 1.2: Primary energy consumption in the EU, Data from: [4]

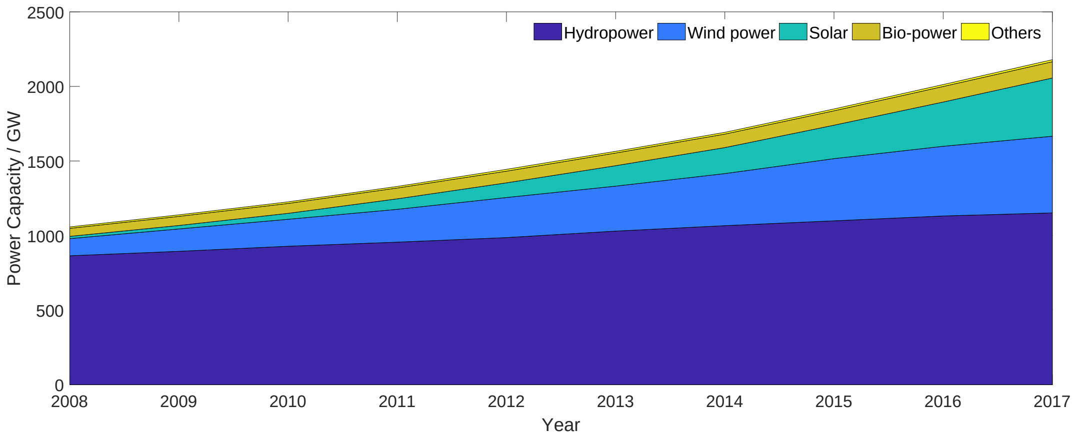


Figure 1.3: Global renewable power capacity, Data from: [5]

From the political point of view, it is estimated that current reserves of conventional oil and gas will be largely depleted by 2100 [10]. Due to the basic economics of supply and demand, it is expected that during this century fossil fuel prices will continue to rise. From the perspective of the UK, local production of fossil fuels fell for 15 successive years prior to 2014, leading to a dependency on energy imports. In 2014 the UK imported nearly 50% of the primary energy that it consumed [11]. This lack of self-sufficiency means the UK, and most other EU countries in a similar position, will have very little control of the price they pay for raw fossil fuels over the next century. Furthermore, the depletion of fossil fuel reserves leaves the UK exposed to regional instability and uncontrollable events [12]. Increasing a nations share of local renewable energy generation is likely to decrease widescale trading of fossil fuel resources and hence lower exposure to random events and price fluctuations [13].

From the energy dispatch point of view, the matching of energy supply and demand is expected to become a more difficult task due to the growth in uncontrollable energy generation from stochastic renewable resources such as solar or wind. Diversification of energy supply alongside an increase in local and grid level energy storage capacity is required to mitigate the potential problems associated with a low-carbon, future energy system [14]. A further method of mitigation would be the closer integration of energy systems at a wider supranational level such as the EU's Energy Union [15]. Closer integration would provide a more dynamic energy trading system, reduce the requirement for curtailment, and increase supply diversity. It is estimated that closer coupling of the EU's electricity markets could save €3.9 billion/yr [16].

1.1.3 Energy and the Built Environment

Building energy consumption is an important sector in both the current and future energy landscapes given that it is estimated to account for 40% of the total EU energy consumption [17]. Significant effort has been placed on the tightening of building standards and comprehensive renovation of existing housing stock to make buildings more efficient through legislation such as the Energy Performance of Buildings Directive (EPBD) [18]. This has largely led to policies of improved insulation, higher efficiency boilers and building integrated renewables. However, while energy efficiency improvements within buildings is a worthwhile goal, progress on decarbonisation of heating and cooling in the built environment is lagging, relative to progress made in the power sector [7]. Improving building energy efficiency alone will not be sufficient to hit 2050 carbon reduction targets [19].

The majority of European buildings are equipped with gas boilers to generate hot water or steam, which is distributed throughout the building. Whilst gas is often viewed as the transition fuel [20], ultimately, to make significant progress on reducing emissions, gas will also have to be phased out of use within buildings. Current emphasis has been placed on the electrification of heating through electrical heaters or heat pumps, the use of biogas or biomass driven cogeneration units for improved efficiency, the conversion of the gas network to include more hydrogen or the use of district heating networks in densely populated areas [19, 21, 22].

1.2 Key Drivers

The wider context in which this research is carried out has been discussed in Section 1.1. This section will aim to outline the specific, key drivers, partially resulting from this context, for the work carried out in this thesis.

1.2.1 Energy Decentralisation

As eluded to in the Section 1.1, the current energy infrastructure requires a large overhaul. Previously, electricity generation was concentrated in relatively few, large-scale, fossil fuel power plants. The electricity generated from these power plants is then distributed via a nationwide distribution network. Similarly, gas is provided to the majority of consumers from which heating is provided through local gas boilers [23]. Due to the fundamental changes occurring in the energy supply mix, such as the inclusion of small scale renewable resources, this nationwide, centralised, energy supply model relied upon for over a century no longer stands [24]. As consumers are encouraged to generate their own energy by exploiting local renewable resources they become 'prosumers' requiring a paradigm shift in the relationship between the distribution network and the individual. At this point energy exchange becomes bi-directional and much more dynamic and complex than the existing centralised model.

This dynamism is one of the driving forces of the 'microgrid', which is an interconnected energy network at a community level with its own energy supply, demand and distribution system that is often also connected to the national grid [25]. The interconnection of several, intelligent microgrids will form the backbone of the proposed 'smart grid' [26]. It is proposed that intelligent management of interconnected energy systems at a local level can aid the integration of renewable resources, reduce energy losses due to reduced transportation distances, and reduce emissions [27]. Furthermore, there is the potential to integrate previously distinct energy vectors to allow truly holistic energy management. A multi-vector energy approach becomes more pivotal as energy networks become more interconnected. For example, cogeneration units can produce heat and electricity from natural gas, heat pumps provide heat energy from an input of electricity and power-to-gas systems can produce hydrogen to fuel cars or synthetic natural gas for combustion or stored for later use. Only by taking a holistic, entire network approach can optimal energy management be achieved [28].

To deliver heating and possibly cooling energy to buildings within a microgrid, district heating and cooling networks (DHC) are becoming increasingly popular [29]. DHC centralises the generation of a community heat energy generation and distributes via the medium of water or steam through a piping network. Benefits of this approach include an increased diversification of heat energy supply, the ability to incorporate cogeneration or trigeneration units bringing with them greater efficiency, and the capacity to incorporate previously wasted energy sources such as excess heat from industry and waste incineration plants [30]. The next generation of DHC aims to transition towards lower temperature flows to reduce energy losses, integration with modern energy efficient buildings, better control through advanced planning and prediction of demand, and they must be integrated and managed holistically with additional energy vectors [31].

1.2.2 The Growth of Data

Implementation of the smart grid or smart energy networks can only be achieved if facilitated by the application of accompanying, advanced ICT infrastructure [32]. A more complex energy system will require increased monitoring at a microgrid level to inform facility managers, in the clearest possible way, the appropriate steps to take. At a district-level much information is captured through Supervisory Control and Data Acquisition (SCADA) systems [33]. For larger, more complex buildings, a Building Management Systems (BMS), also based on SCADA principles, will be in place to record several important variables such as zone-level room temperature, disaggregated energy consumption, occupancy, and indoor air quality [34]. On a residential scale, there has been a concerted effort to install ‘smart meters’ which can provide more regular reporting of building electricity and gas consumption. An estimated €45bn will be spend by EU member states by 2020 to roll out smart gas and electricity meters [35]. Smart meters are expected to make the direct cost of energy consumption more tangible to consumers and therefore encourage behaviour change. In addition they could pave the way for more advanced Time of Use (ToU) tariffs to encourage voluntary load shifting. The data produced by smart meters could also provide opportunity for microgrid energy management and utility companies in learning usage patterns to assist the scheduling of energy supply [36].

As well as the more traditional metering devices, there has also been an explosion in internet connected devices capable of measurement, data recording and automated controls due to the Internet of Things (IoT) paradigm [37]. This greatly increases the wealth of data available in a smart building or smart district. There is potential to integrate this wider, contextual information with existing building-level and district-level energy monitoring to provide a more holistic view of a smart energy system and more actionable observations. This vast array of sensing capability can be leveraged by energy management systems at both a district [38] and a building level [39].

Recent state-of-the-art reviews by Keirstead et al. [40], Allegrini et al. [41] and Howell et al. [42] argue for increased data integration within smart cities and districts. Allegrini et al. [41] specifically argues that BMS need to embrace urban-scale data to improve building energy management. Also it is essential that buildings are viewed and managed as an integral and active part of a wider district and urban energy system. A city-level integration of data, analysis and strategy can lead to opportunities by linking different sectors for mutual benefit and holistic city governance. Examples include linking energy and municipal waste through anaerobic digestion or waste incineration, energy and the economy though city level Energy Service Companies (ESCo's), and the energy and transport sector through electric vehicles. Potential benefits can only be reaped through city-level open data integration [43].

1.2.3 The Need for Demand-Side Management

Another consequence of the growth of uncontrollable energy generation and energy decentralisation is the greater requirement for demand-side management. Previously, the energy sector was demand-led whereby the fully controllable, and centralised energy supply was managed to follow the largely uncontrollable demand. As greater uncertainty and lower control can be exerted on energy supply, a paradigm shift must be made towards a system in which both supply and demand are partially controlled to ensure a continued energy balance. At a local microgrid level, demand-side management can take greater emphasis if the microgrid is operating in 'islanded' mode where the microgrid is not connected to the main national grid and is self sufficient from an energy perspective. Even when a microgrid is not operating in 'islanded' mode, some level of demand-side management may be necessary to maximise the economic benefit from local renewable resources rather than selling excess energy to the national grid at relatively low prices. There are two broad categories of demand side management; market-based and physical-based [44]. Market-based demand side management is largely aimed at developing voluntary consumer behaviour change via financial incentives. This could include ToU tariffs, dynamic real-time pricing, and peak pricing alerts. By charging higher prices during peak periods, users will voluntarily limit their consumption during these periods, helping to balance the grid. The implementation of these more complex energy tariffs would be facilitated by wide-scale deployment of smart meters as discussed in the previous section.

Physical-based demand-side management is a more formal, contractual, relationship between the energy network and generally, very large, industrial consumers. During critical periods the energy grid sends out binding demands for specific clients to shed demand to balance the network. Whilst this sort of arrangement has previously only been available to a small number of very large consumers, it is theorised that due to the decentralisation of energy management, these arrangements could be available to small-scale consumers aggregated together at microgrid level [45].

A significant factor in tackling the challenge of meeting fluctuating demand could lie with improvements in energy storage technology. Traditional means of large-scale electricity storage lay in pumped hydro and compressed air energy storage. However, in recent years there has been a wealth of development in the use of batteries for grid ancillary support [46]. If the expected growth in electrical vehicle ownership increases then these vehicles could also be viewed as an additional bank of energy storage capacity through vehicle to grid interactions [47]. These types of energy storage technologies are economically viable and appropriately scalable for integration at microgrid level as well as existing national-scale solutions.

Aside from emerging energy storage solutions, demand flexibility can provide similar short-term effects. It is estimated that 247GW of consumption is adaptable to be brought forward and 93GW of consumption can be delayed across the whole of Europe [48]. Similarly, in 2010 it was estimated that a quarter of demand in the US could be dispatchable if utilised appropriately [49]. Although, to achieve this level of demand flexibility, significant regulatory framework must be provided to ensure consumers are appropriately incentivised and compensated for the flexibility services they provide to the local or national grid [50].

1.2.4 The Rise of Artificial Intelligence

Exact definitions of Artificial Intelligence (AI) are debated within the AI community and are often rather loose and vague. One such definition is provided by Luger [51]: *"Artificial intelligence (AI) may be defined as the branch of computer science that is concerned with the automation of intelligent behavior."*. In this thesis, a very broad definition of AI will be taken to include (but not limited to) applications of machine learning, expert systems, agent-based systems, advanced optimisation, and modelling. AI is set to revolutionise almost all sectors of society over the coming decades including the fields of manufacturing and robotics [52], medicine [53], social care [54], and energy [55].

A focus on AI at urban scale has led to the concept of 'Smart Cities'. AI has facilitated improvement in large scale transportation networks through adaptations such as dynamic traffic lighting controls and increased predictive analytics for public transport arrival times [56]. Analytics powered by AI is equally applicable in for the smart water and energy sector. Increased instrumentation and interconnectivity can allow automatic analysis for fault detection and extreme events within water, transportation and energy networks. Through optimisation and modelling, mitigation measures can be implemented to minimise losses and the impact to the public [57].

At a 'Smart Home' level, AI can be leveraged to predict factors such as user demand and building integrated solar energy generation [58, 59]. To extract the largest value from small scale renewable energy generation, users need to maximise the self-consumption of this energy. It is unreasonable to expect the consumer to micromanage their building energy consumption on an hourly basis, instead autonomous, intelligent agents can be used to optimise the energy generation in conjunction with building scale energy storage devices [60]. Residential level, solar connected battery storage has become much more available in recent years from companies such as Tesla, Nissan and Ikea. In the near future, AI within a smart home will become more necessary with the introduction of electric vehicles and vehicle-to-grid systems [61]. The automated building controller will have to balance and predict the requirement to maximise solar self consumption, ensure electric vehicles are charged when they are needed and maximise the economic gain to the consumer.

1.2.5 User Perceptions, Security and Privacy

Developing smart homes and allowing users to take a more active role within energy markets is viewed as a key component of achieving the smart grid vision by policy makers [62]. Smart home products are now widely available commercially through products such as British Gas's Hive and Google's Nest. A recent survey of over 1000 UK homeowners found that users perceive smart home services "through an energy management lens" [63], and believe that these devices can save them energy and money. However, participants did have concerns about increasing their dependence on systems and technology and hence a loss of direct control on appliances. An additional concern relating to smart meters is perceived loss of privacy and security epitomised by a fear of 'Big Brother' watching [64].

The potential growth in smart meters and smart home devices could provide opportunities for third party, Energy Service Companies (ESCo's) to provide an energy management and automation solutions to consumers. External companies could utilise modern high performance computing to offer a cloud-based, virtual energy management solution. This proposition brings with it an obvious conflict with users concerns of privacy and security. The anonymisation of data, storage location and sharing of data with additional companies are likely to be key questions for ESCo's to answer to assuage consumers concerns. Ultimately, for this model to thrive within a liberalised energy market, service providers will have to make a clear value proposition which translates to tangible benefits for the consumer (likely financial) to overcome their concerns related to privacy.

A technological solution that could aid in fostering trust within consumers is the recent advances in blockchain. Previous iterations of blockchain enabled crypto-currencies such as Bitcoin. Blockchain provides an open, verifiable, distributed, and immutable record of interactions and transactions. Blockchain technology has now moved beyond just crypto-currencies to theoretically enable smart contracts and peer-to-peer energy trading, an example of which is being developed by LO3Energy deployed to a small microgrid in New York [65]. It is envisaged that a blockchain enabled smart home could enhance the security and privacy of a IoT based smart home system [66]. Furthermore, it could enable a basis for trustworthy transactions between users within a smart grid environment without the requirement of a third party facilitator [67].

1.3 Problem Statement

The key drivers discussed in Section 1.2 all combine to form a unique opportunity for a step change in energy management at building, district, national and supranational levels. The way energy has previously been managed is increasingly outdated. A new generation of controllers must be deployed to transition towards a holistic, predictive and pre-emptive management approach leaving behind the top-down, reactive, rule-based approaches of the past. Energy decentralisation and growth in renewable energy generation requires more co-operative, localised energy management to fully maximise the economic and environmental benefits of these systems. This can be facilitated by a suite of modern AI techniques such as machine learning-based prediction and modelling, in conjunction with advanced optimisation and scheduling strategies. This sort of optimal control requires a wealth of sensors, actuators and data, which is more commonly available due to the increased penetration of smart meters and IoT devices.

1.4 Research Objectives

Following the key drivers and problem statement, the aim of this research is to pave the way for the next generation of energy management controllers. These controllers must be increasingly context-aware and adaptable to changing external environments. By taking into account external factors, such as predicted weather conditions, district demand, renewable supply, energy tariffs and demand response events, a more holistic energy management solution can be achieved. The specific target of this thesis is to test a central hypothesis through decomposition into several research questions. The central hypothesis to be tested is:

"Simultaneous control of building and district energy systems can achieve greater energy savings and environmental benefits by operating cooperatively and increasing their awareness of external, contextual building information such as weather conditions, occupancy, energy generation, or energy prices."

To evaluate the central hypothesis, the following research questions have been formulated:

1. How can the components found within a district energy system be modelled for the purposes of operational optimisation?
2. Can predictive control of building energy demand with consideration of external factors lead to reductions in energy cost and improve demand-side flexibility?
3. Can taking an optimisation-based approach to the control of district heat generation improve upon existing rule-based priority order strategies?
4. Can integrated, holistic control of both energy supply and energy demand lead to greater economic and environmental benefits than independent control?

5. Can a semantic web approach ease the deployment of advanced energy management strategies on a wider scale and aid integration with additional domains?

The origin and relevance of these research questions will be made clear in Chapter 2 through a thorough literature review and the method by which they will be answered will be detailed in Chapter 3.

1.5 Thesis Outline

This chapter has aimed to provide the wider context and background as to the motivation and significance of the research provided in this thesis. The following chapter, Chapter 2, provides a thorough review of the existing body of literature. It is split into four main parts; the modelling of building energy, the optimisation of building energy demand, the modelling of district energy systems at a component level, and optimisation strategies applied at a district level. From this review, the foundation of the research gap will be developed.

Chapter 3 will detail the overarching methodology and approach to carrying out the research described in this thesis. It will discuss the philosophy behind the research, clarify the method by which the research questions will be answered, and report how the work throughout this thesis has been validated. This chapter will also introduce the core theory behind the main components used throughout the thesis, namely artificial neural networks, genetic algorithms, and model predictive control.

Chapter 4 specifically addresses energy management at a building level. This chapter will outline the methodology behind the zone-level optimisation strategy leading to contribution number 1 and go towards answering research question 2. This is evidenced by a simulated case study applied to a small office building in Cardiff.

Chapter 5 instead targets energy management from the supply-side at a district-level. It introduces an optimisation strategy to schedule the generation load from several energy conversion technologies and a thermal energy storage tank. It takes a predictive and pre-emptive control approach improving upon a static, rule-based, priority order control system. This is evidenced through application on a simulated eco-district.

Chapter 6 effectively integrates the methodology of both Chapter 4 and Chapter 5 to simultaneously and holistically manage both energy supply and energy demand. This is achieved through scheduling the energy conversion technologies as well as the heating set point schedule of the office building within the district. Control of both supply and demand provides additional flexibility to the district controller to shift load to reduce cost to the energy centre as well as consumers.

Chapter 7 explores the role semantic and ontologies can play to translate the ad-hoc optimisation strategies into scalable and robust energy management solutions. It will also discuss additional research fields that can supplement the research carried out in this thesis.

Chapter 8 concludes this thesis by re-visiting and answering the research questions provided in this Chapter. Through answering these research questions the central hypothesis can be tested. In addition, the main contributions to the body of knowledge resulting from this research are summarised.

1.6 Contribution

This thesis makes a number of contributions to the wider body of knowledge.

1. A contribution is made within the field of building-level energy management with the development of a zone-level heating optimisation strategy. This optimisation combines zone-level artificial neural networks, which model the thermal characteristics of each zone, with a genetic algorithm with the objective of minimising energy consumption or energy cost. The methodology is perceptive of external influences such as weather conditions, occupancy and energy tariffs.

2. At a district-level, a framework to optimise the heat generated within a multi-vector district heating system is developed. Crucially, part-load characteristics, prediction of energy demand, prediction of uncontrollable energy supply, and an intermediate error management procedure is included to form a realistic and challenging case study.

3. An optimisation strategy that predictively controlled both energy supply and energy demand within a complex district energy system has been provided. By considering both supply and demand as partially controllable, and approaching the energy management challenge from both a building and district scale, significant cost and energy savings were achieved.

Naturally, the described contributions have been assembled sequentially over the course of the PhD programme. The main contribution described in this thesis is therefore point 3 which effectively integrates the contributions of point 1 and 2 to form the most substantive piece of work.

2 | Literature Review

This chapter aims to provide a comprehensive review of all aspects required in the holistic management of a modern, complex, energy grid. Initially, this chapter will focus on energy modelling at a building-level and then optimisation at this scale. Literature focussing on a building-level tends to be more concerned with control of building demand rather than explicitly including management of energy supply. To achieve a more holistic energy management strategy, energy at a wider district-level must also be considered. Therefore, Section 2.3 and Section 2.4 consider modelling and optimisation of district-level components and microgrids. As a result of reviewing the existing body of literature, the research gap and motivation for the research questions addressed in this thesis will be explored in Section 2.5.

2.1 Building Energy Modelling

Buildings need to be considered as integral and active parts of an urban energy system and therefore need to be modelled accurately. Building loads (heating and cooling, hot water and electricity consumption) depend on a number of different factors e.g., weather conditions (solar radiation, dry-bulb air temperature, wind speed), thermal properties of building's fabric, occupants' behaviour, the installed energy system, operational schedules, etc. These interdependencies increase the complexity of the problem, and therefore accurate prediction of building energy consumption can be a challenging task. However, several different building modelling techniques currently exist with different advantages and disadvantages. These modelling techniques can broadly be categorised as white box, grey box, or data driven models [68].

2.1.1 White Box Modelling

White box or Engineering methods are based on using physical principles to calculate thermal dynamics and energy behaviour of a building or system [69]. Engineering models can be divided into the following categories; detailed methods and simplified methods [69]. Simplified methods can include degree-day, bin methods, etc. and are steady-state methods. These methods are predominately useful when the building energy consumption is more dependent on the building fabric. Detailed methods (e.g. TRNSYS, DOE-2, EnergyPlus) often enable users to evaluate design with reduced uncertainties, because of their multi-domain modelling capabilities [70]. Detailed simulation models can produce accurate results; however, they require an extensive amount of building and environmental data for modelling a building and its systems. Modern research efforts are targeting the use of 3D laser scanning and photogrammetry techniques to quickly realise an accurate as-built representation of building geometry on a district scale [71, 72]. However, digitisation and subsequent generation of energy models remains a time-consuming task requiring significant manual intervention [73].

Furthermore, these initial building energy models do not tend to perform well in predicting energy consumption of occupied buildings as compared to the design stage prediction [74]. Extensive calibration efforts are often required during the operational phase to adjust the model to reflect reality. This requires widespread metering, categorised spatially and by end use at small time intervals. However, once a calibrated energy model has been completed it can output an exhaustive range of variables from building level total electricity consumption down to the air flow rate of a single zone. Detailed simulation models tend to be more computationally expensive and therefore, are generally considered not suitable for near real-time optimisation problems.

Once a basic energy model has been constructed using the known geometry, construction materials, energy systems and basic rule-of-thumb internal gains estimates; significant efforts are required to calibrate a model. While no agreed upon, universal, methodology has been achieved there are a number of literature reviews on the subject [75–77] and a number of proposed methodologies [78, 79]. However, many of these methods are still manual, iterative and time consuming. They often involve identifying the most sensitive parameters that impact on energy consumption using probabilistic analysis such as a Monte Carlo simulation [80]. From this the modeller can allocate most effort to iteratively tuning these parameters [79]. Many of these methodologies aim to estimate a level of uncertainty associated with the resulting building model also [81]. A recent step has been made through the development of 'Autotune' for Energy Plus models [82]. This method uses an evolutionary algorithm to tune selected important variables aiming to minimise the error between the Energy Plus output and measured data. However, given the number of 'tuneable' parameters in a typical building and given that a population-based optimisation method is used; this led to a very large number of evaluations and hence simulations. To address this, the study used several high-performance computing techniques and supercomputers, which made this method inaccessible to ordinary practitioners. The resulting calibrated model, when applied to a complex building, achieved an accuracy of CV(RMSE) = 11.82% and MBE = -1.27%, equivalent to a manual calibration.

A calibration methodology was implemented in [83] and applied to two simulated building and one actual building. Influential modelling parameters were first identified with best guess estimates inputted. This was followed by a course and fine grid Monte Carlo simulation to refine and improve calibration solutions. The resulting calibrated model achieved a CV(RMSE) value of 6-8% when comparing simulated vs actual monthly electricity consumption. Monetti et al. [84], used a particle swarm optimisation, PSO, to calibrate several parameters of an EnergyPlus building. The authors considered infiltration, equipment power, ground temperature, material properties and thicknesses as variables. Once calibrated, a CV(RMSE) of 0.19%-20.40% was reported for hourly heating energy consumption comparison of several zones. A two-stage, building energy modelling procedure was carried out in [85]. The initial stage involved detailed inspection of as-built building documentation and surveys of internal loads. The second stage required a more thorough interrogation of key BMS data and occupant surveys. The completed model complied with ASHRAE Guideline 14 accuracy limits for modelling of heat pump electrical demands, heat pump thermal output, building electrical consumption, natural gas consumption, and indoor zone temperature.

2.1.2 Grey Box Modelling

Grey box models are hybrid models; they use simplified physical descriptions to model building and/or building energy systems. The coefficients of the models are identified based on the operational data using parameter identification methods. A simple example of this type of models is the Resistor-Capacitance (RC) model; in which an electrical circuit analogy is used to model heat transfer through a wall. This method simplifies the problem through a linearization of the equation and hence reduces the computational time [86]. These models are mostly used as a good compromise between modelling accuracy and computational time.

A methodology to develop the simplest, yet suitably accurate, RC model for a single storey case study building in Denmark was explained in [87]. It aimed to model the indoor temperature as a function of solar irradiance and heating input. The final model achieved errors less than $\pm$ 0.1°C but from an optimisation perspective, prediction of heat consumption as a function of set point temperature and weather would be more useful. Ahmad et al. [88] [89], developed an RC model for a two-room building. The model was used to output the energy consumption of the building. The authors then developed an MPC controller to save energy consumption while maintaining thermal comfort. Similarly, Berthou et al. [90] tested four different configurations of RC models each increasing in complexity. The authors found the 6 resistors, 2 capacitance model to be the best compromise between accuracy and complexity. TRNSYS data was used to tune the RC model parameters which used occupancy, ventilation, temperature set point and solar gain as inputs to predict indoor temperature and heating and cooling demand with resulting fit values of 88% and 89% respectively. Zhou et al. [91], developed not only a building load prediction model but also weather modules to provide the inputs to the building load RC model, hence developing an online, day-ahead, prediction service. Grey dynamic models were used to predict outdoor temperature and relative humidity which were then used to forecast the solar radiation. The predicted solar radiation was then used as an input to forecast building cooling demand with an eventual R^2 value of 0.91-0.93. However, the number of testing days included was quite limited, and weather forecasting errors had an impact on the eventual energy demand prediction.

Reynders et al. [92], derived several RC models to emulate a more complex, white box Modelica model. First to fifth order RC models were tested along with different training data sets, the addition of noisy data, and using alternative, more easily measured, inputs. The study found that using solar irradiance on vertical planes could effectively take the place of solar gain data and building electrical demand could be used as a proxy for internal gains data. However, the resulting grey box model is only validated against a white box model of a generic Belgian house rather than a real case study. A toolbox design for the streamlining and semi-automation of the development of RC models for model predictive control is outlined in [93]. The software aids the data handling, model selection and parameter estimation, however, achieved poor validation results in one case study due to inappropriate training data. A dynamic, thermal RC model was integrated with an existing stochastic, Markov-Chain, electrical demand and occupancy model in [94]. Building demand, hot water cylinder, gas boiler and heating control models were all integrated and received active occupancy profiles based on a UK building use survey. However, this study was aimed at producing generalised, aggregated, probabilistic thermal demand of several building rather than specifically for real-time optimisation like the other studies in this section.

Afram and Janabi-Sharifi [95], developed a detailed grey box model of a residential HVAC system comprised of subcomponent models for an Energy Recovery Ventilator (ERV), Air Handling Unit (AHU), buffer tank, radiant floor panels, and a Ground Source Heat Pump (GSHP) based on energy balance equations. Once the model parameters had been identified, only zone and buffer tank set points as well as outdoor air temperature were required as inputs. The authors argued such a model would be prime for use in conjunction with MPC.

2.1.3 Data Driven Modelling

Data driven models are input-output models based purely on historical data with no representation of the underlying physical characteristics of a system. These can include purely statistical regression models, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest models in addition to others. Data driven models have been used extensively in the literature to predict or calculate a wide range of variables key to building optimisation and control such as electricity demand, heating demand, indoor temperature, and predicted mean vote (PMV - a measure of thermal comfort). Summaries of these types of computational intelligence techniques can be found in [96, 97]. The above methods rely on a training period that uses extensive amounts of data. This means that historical data needs to be logged for an extended period or simulation models need to be used to produce substantial amounts of realistic data.

Much of the literature based on creating ANN to accurately predict building data emphasises the need to ensure the most appropriate inputs are used as well as the optimal architecture and internal function are selected. Ferreira and Ruano [98], uses a GA to find the optimal architecture of an ANN to predict the climate of a greenhouse, the resulting model can then be used for optimisation processes. A complete example of selecting functions between each layer can be found in [99]. The resulting model could predict electricity consumption, thermal energy consumption and PMV in a sports facility. From this, the HVAC system could be optimised using a model predictive control technique. Predicted Mean Vote (PMV) is a measure of thermal comfort ranging from -3 (very cold) to +3 (very hot) with 0 being the ideal average thermal comfort for a group of occupants. It is normally a complicated parameter to calculate requiring seven (often difficult to measure) variables to be used as inputs to Fanger's equation. Both [100, 101] produce ANN based solutions to calculate

PMV without the need to solve Fanger's equation.

Bagnasco et al. [102], uses an ANN to forecast the electricity demand of a hospital in Turin. Considered inputs include the day of the week, time of day, loads at the same timestep from the previous day and from seven days ago, outdoor temperature, and whether or not it is a weekday. Similarly, [103], forecasts day ahead electricity consumption at 15-minute intervals using an ANN. It only considers five input variables, day type, time of day, operational condition, outdoor temperature and outdoor relative humidity but achieves very good prediction accuracy with CV(RMSE) in the order of 8-10%. A regression-based, data analysis approach was used in [104] to find a correlation between weather and occupancy variables to three electrical load types (appliance, ventilation, and cooling). The authors found that work hours, occupancy and outdoor temperature were the most important variables in calculating the electrical loads and using fewer predictor inputs resulted in lower errors. The use of ANN and Random Forest algorithms was compared in [74] for the prediction of HVAC electrical consumption of a hotel in Madrid. Considered inputs included weather variables, date and time variables, the number of guests and the number of rooms booked. The ANN was shown to marginally outperform the Random Forest model however the authors argued that Random Forest based methods are easier to tune. A comprehensive and systematic review of electrical load forecasting in buildings, [105], concluded that black box models such as ANN or SVM are well suited to the task.

An auto-regressive model with exogenous inputs (ARX) and a neural network auto-regressive model with exogenous inputs (NNARX) were compared for their suitability to model indoor temperature in [106]. The model aimed to predict the indoor temperature of a building using previous indoor temperature, outdoor temperature, solar radiation and heating power as inputs. The NNARX model significantly outperformed the linear ARX model, and once pruned using the optimal brain surgery algorithm achieved an SSE of 0.906. Royer et al. [107], used a second order state space model to predict the indoor temperature of zones also using outdoor temperature, solar radiation and HVAC operation as inputs. The model proved itself to be adaptable to different buildings but achieved poor results in colder climates.

Deep learning techniques have been more widely applied to building energy consumption than other components within the energy sector. Deep learning methods are commonly based on extensions of a simpler, more shallow, ANN and are well suited to complex tasks such as image processing. Both [108] and [109] applied deep learning methods to the same dataset. The trialled methods included Long Short-Term Memory (LSTM), Conditional Restricted

Boltzmann Machines (CRBM) and Factored Conditional Restricted Boltzmann Machines (FCRBM) with the aim of forecasting residential electricity consumption over varying time horizons. In most scenarios the deep learning models were able to outperform more traditional machine learning models. Fan et al. [110], tested different feature extraction methods combined with several modelling techniques ranging from multiple linear regression to machine learning techniques to Deep Neural Networks (DNN) to predict building cooling energy consumption. They found that application of a deep learning unsupervised feature extraction technique could improve model performance compared to more traditional methods. However, in this case study, it was concluded that a truly ‘deep’ model was not optimal, and the cooling load was best predicted by an Extreme Gradient Boosting (XGB) model. DNN were also used in [111] for forecast the electricity consumption of 40 commercial buildings in South Korea. The DNN were shown to consistently outperform shallow neural networks and a double seasonal Holt-Winters (DSHW) model across different building use categories.

2.1.4 Summary

A summary of the reviewed literature can be found in Table 2.1. This review is in agreement with previous reviews that white box simulation models are not suitable for sub-hourly, real-time optimisation. The computational time is too great to be used as an evaluation engine, and they require an expert to create and then calibrate the model using vast amounts of static and dynamic building data. Both grey box and data driven building models have been proven to be effective in the reviewed literature for modelling a wide range of building variables. For use in conjunction with building or district optimisation, it is assumed that building demand prediction and indoor temperature or thermal comfort would be the most useful model outputs. From this, the simplified building models could be used as an evaluation engine in the optimisation algorithm testing the building response to chosen control signals.

The methods by which these models are generated on a wide-scale and at speed remains an outstanding question. If data driven and grey box models are to be used, then the capture and long-term logging of sensor data from existing buildings must be improved and should be envisaged during the design phase as standard practice. However, if based solely on historical data, these models cannot be used to provide predictions based on hypothetical changes made to the building systems as no data would be recorded for such a scenario. An alternative process to overcome this would be to first produce a white-box

Table 2.1: Building modelling literature summary

Ref	Method	Input Parameters	Output Parameters	Model Accuracy	Real Case Study
[82]	EnergyPlus Autotune	Building Geometry, Material Properties, Occupancy, Lighting, Equipment and HVAC Gains and Schedules	Electricity Consumption	CV = 11.82%, MBE=-1.27%	No
[79]	EnergyPlus Manual Tuning	Building Geometry, Material Properties, Occupancy, Lighting, Equipment and HVAC Gains and Schedules	Electrical and Gas Consumption	GOF = 5-7%	Yes
[84]	EnergyPlus Manual Tuning	Material Properties, Lighting, Equipment and HVAC Gains, and Ventilation	Heating Consumption	CV=0.19-20.4%, MBE=-0.14-0.83%	Yes
[85]	EnergyPlus Manual Tuning	Building Geometry, Material Properties, Occupancy, Lighting, Equipment and HVAC Gains and Schedules, Occupancy Survey	HP Electricity Consumption, HP Heat Supply, Indoor Temp, Electrical and Gas Consumption	CV=7.3-25.1%, CV=18.2-33.5%, CV=12.4-28.7%, CV= 6.3-16.5%, CV=4.5-14.1%	Yes
[87]	RC Grey Box	Solar Irradiance, Heating Input, Static Parameters	Indoor Temperature	Absolute Error $<\pm$ 0.1 °C	Yes
[91]	RC Grey Box	Outdoor Temp, Humidity, Solar Radiation, Internal Gains	Building Load	R^2 = 0.91-0.93	Yes
[92]	RC Grey Box	Solar Irradiance, Electrical Consumption, Outdoor Temp, Set Point Temp	Heating Demand, Indoor Temp	-	No
[93]	RC Grey Box	Outdoor Temp, Horizontal Solar Irradiance, Heating Load	Indoor Temp	RMSE = 0.33K	Yes
[95]	RC Grey Box	Buffer Tank and Zone Set Point, Outdoor Temp	Ventilation & AHU Outlet Temp, Tank & Zone Temp, Radiant Floor and GSHP Return Temp	R^2=0.996-1.000, CV=0.010-0.069	Yes
[99]	ANN	Minute, Hour, Day, Month, Occupancy, Humidity, Pool Temp, Indoor Temp, Outdoor Temp, Air Flow Rate	Electrical and Thermal Energy Consumption, and PMV	MSE = 0.0015%	Yes
[100]	ANN	Air Temp, Web Bulb Temp, Globe Temp, Air Velocity, Clothing, Activity	PMV	-	Yes
[101]	RBF ANN	Air Temp, Relative Humidity, Globe Temp	PMV	Absolute Error $<\pm$0.0075	Yes
[102]	ANN	Previous Days Consumption, Previous Week Consumption, Day Type, Timestamp, Outdoor Temp	Electricity Consumption	Mean MAPE = 7%	Yes
[103]	ANN	Operational Condition, Time, Day, Outdoor Temp and Humidity	Electricity Consumption	CV = 7.97-11.06%	Yes

Table 2.1: Building modelling literature summary

Ref	Method	Input Parameters	Output Parameters	Model Accuracy	Real Case Study
[104]	Regression	Outdoor Temp, Daylight, Work Hours, Radiation, Occupancy	Appliance load, Ventilation Load, Cooling Load	RMSE = 7.1-13%	Yes
[106]	ARX and NARX	Outdoor Temp, Solar Radiation, Heating Input	Indoor Temperature	SSE=0.9060 (NARX), SSE=15.0379 (ARX)	Yes
[107]	State Space Model	Outdoor Temp, Solar Radiation, HVAC Operation	Indoor Temperature	Fit = 92-84%	No
[112]	ANN	Outdoor Temp, Time, HVAC Operation, Convective Transfer of Windows	Indoor Temperature	R^2 = 0.97, RMSE = 1.11K	Yes
[113]	NARX	Day of the Week, Time, Outdoor Temp, Set Point Temp, AHU Supply Temp, AHU Flow Rate	Indoor Temperature and HVAC Consumption	CV=0.007868, CV=0.114	No
[114]	ANN	Outdoor Temp, Solar Irradiance, Humidity, Hour, Set Point Temp, Previous Indoor Temp	Energy Consumption, PPD, Indoor Temperature	R^2 = 0.9888, 0.9982, 0.9985	No
[110]	SVR, XGB, DNN	Time, Date, Outdoor temperature, Relative humidity	Cooling energy consumption	CV(RMSE): SVR = 19.0%, XGB = 17.8%, DNN = 20.9%	Yes
[111]	DNN	Outdoor temperature, humidity, solar radiation, cloud cover, wind speed, date and time, previous consumption	Electricity Consumption	Average MAPE = 8.85	Yes

Note - CV (Coefficient of Variation), MBE (Mean Bias Error), GOF (Goodness of Fit), HP (Heat Pump), RC (Resistor Capacitance), RMSE (Root Mean Squared Error), RBF (Radial Basis Function), PMV (Predicted Mean Vote), GSHP (Ground Source Heat Pump), MAPE (Mean Absolute Percentage Error), NARX (Nonlinear Autoregressive Network with Exogenous Inputs, SSE (Sum of Squared Error), SVR (Support Vector Regression), XGB (Extreme Gradient Boosting), DNN (Deep Neural Network).

simulation model of the building in question, calibrate it based on recorded data and building surveys, and run several hypothetical scenarios to form a broader bank of training data from which a data driven model is produced. Currently, this procedure would be highly time consuming and difficult to scale for several buildings, however, there is increased emphasis and legislation requirements around digitisation of buildings through Building Information Modelling (BIM) and energy modelling at design stage.

2.2 Building-Level Energy Management

Most large complex buildings will be equipped with a Building Management System (BMS). These sense conditions in building zones and are programmed with internal logic to take action using various actuators depending on the conditions they perceive and the time of day. However, traditional BMS follow fairly static rules without the intelligence to try new, potentially more optimal, strategies. For example instead of turning on the heating at 8am to have the building at the appropriate temperature by 9am, could the building be pre-heated to avoid a morning spike and possibly reduce overall daily energy consumption? Can occupancy levels be better predicted and sensed to ensure that zones are only heated when necessary? Is the optimal strategy dependant on the current and forecast outdoor conditions? Can load be shifted to coincide favourably with cheap energy periods or local energy generation? These are the typical questions facing the development of more advanced BMS which are vital for reducing energy consumption and improving comfort within buildings. Lee and Cheng [115] reviewed the impact of BMS over 35 years and found that during this period energy savings from BMS have increased from 11.39% to 16.22%. However, a key challenge for the future BMS is the availability, cost and quality of sensors as well as the data management problems that arise from the increased sensing [60]. An excellent review of BMS is provided by De Paola et al. [34] in which the author sets out the ideal BMS and how close current technologies are to that ideal. Figueiredo and da Costa [116], argues that an intelligent, 'interactive' level could be placed above the SCADA-based BMS to provide integrated control over all building systems including temperature control, lighting, water and electricity.

2.2.1 Smart Home Energy Management Systems

Whilst most current BMS are installed in larger commercial buildings, smart energy management in residential buildings is also very important and a growing area of research. We are already seeing 'smart' thermostats like Google's

Nest, which aim to learn users temperature preferences and patterns to save energy. In-home smart assistants such as Amazon's 'Alexa', can leverage the growth in IoT devices to allow smart home coordination of lighting, blind control, heating and cooling, and even appliances such as cookers, vacuum cleaners, and dishwashers. Whilst a user can control devices from a central point there are currently no commercial systems that can centrally coordinate these heterogeneous devices logically with the aim of minimising energy consumption or cost. As commercial systems are relatively new and the literature provides a number of suggestions for possible system architectures. Capone et al. [117] presents the AIM gateway which proposes a communication architecture for devices and sensors within the home. The authors suggest that this could provide better monitoring and prediction for energy suppliers through user profiling. A similar vision for a Home Energy Management System with a series of devices connected to a smart meter or central controller in both [118] and [119]. The authors argue that the management and scheduling of these devices could be outsourced to a third party which would utilise intelligent analytics to save the consumer money. There is also emphasis that the scheduling strategies need to consider demand response within their control logic.

An intelligent BMS is simulated in [120]. The BMS is assumed to control household appliances, the heating, local PV resources and sense outdoor conditions. A grey box, resistor-capacitance, RC, thermal model of a small house is created to simulate the indoor temperature depending on the heating strategy. By shifting the operation of controllable appliances, the smart BMS made significant cost savings. Smart household scheduling is also addressed in [121]. This also controls the heating and controllable appliances but uses a Model Predictive Control, MPC, technique and utilises electrical battery storage which it theorises could come from a plug-in electrical vehicle. The solution is simulated in several climates and is shown to save the user up to 20%. However, this strategy assumes perfect weather forecasting so the saving, in reality, is likely to be reduced. Yuce et al. [122] combined the use of an Artificial Neural Network, ANN, and a Genetic Algorithm, GA, to schedule domestic appliances to ensure maximum utilisation of local renewable resources. The use case presented is based on a small holiday home in Southern England which has on-site PV and wind production. When grid energy reductions of 10%, 25%, and 40% are imposed on the building, the idle renewable generation is clearly reduced. Zucker et al. [123], outlined the architecture of a cognitive building control system. Cognitive algorithms aim to mimic the way the human mind thinks through storing historical experiences and selecting the most appropriate decisions based on previous actions.

A Home Energy Management System (HEMS) was developed in [124]. The control scheme simulated 26 electrical appliances within a home with the aim of controlling thermal comfort and minimising the electricity cost to the consumer. When a solar PV system and battery storage is added to the home, the control algorithm effectively shifts load off peak to lower price periods saving around 17% in cost. Huang et al. [125] introduced an adapted Particle Swarm Optimisation (PSO) to control various devices within a HEMS including energy storage, deferrable loads, thermal loads and interruptible loads within a dynamic energy pricing structure. The PSO provided near-optimal solutions which are checked for feasibility against a number of constraints. If the constraints are breached, an adaptation is made to optimisation procedure where the constraints are repaired before continuing with the optimisation.

Mohsenian-Rad and Leon-Garcia [126] argued that dynamic energy pricing tariffs often confuse average consumers. Therefore, the study aimed to develop a simple and automatic optimisation procedure to predict energy prices and schedule the operation of each household appliance based on linear programming. The optimisation strategy must balance the minimisation of electricity cost and the waiting time of the consumer (and hence comfort). The more flexible the user chooses to be, the higher the energy savings achieved. Electricity pricing uncertainty while scheduling household appliances was also considered in [127]. In this scenario the user could purchase electricity on the day-ahead market or in real-time with fluctuating prices. The dual time horizons required the problem to be decomposed into sub-problems and solved using a stochastic gradient approach.

An approach which may be a natural fit to control the disbursed range of smart home appliances is a Multi Agent Systems (MAS) approach. This approach would assign home appliances each with an intelligent agent. Each agent is perceptive of it's environment, able to communicate with other agents, and programmed with a control logic to manage it's appliance effectively. These agents must be coordinated by one or several management agents to ensure cooperation and holistic control. The nature of the distributed approach makes this strategy scalable and adaptable to new appliances, robust if single lines of communication fail, and able to assimilate the inherent heterogeneity of smart home devices.

A MAS architecture for home energy automation is proposed in [128]. Three energy services are defined; end use by appliances, intermediate such as energy storage, and support which is energy supply. Each of these services is further separated into permanent or temporary services which have different constraints and attributes. An alternate MAS architecture was deployed in

[129] for an eco-house with several renewable energy sources available and the capacity to operate disconnected from the main grid. The operation of the MAS control is demonstrated in a case study with several wind turbines, PV panels and battery storage. The MAS control system effectively matches supply and demand, however, the output from the renewable generators and the building demand is known accurately in advance. Zhao et al. [130] demonstrated a MAS system with agents to manage a multi-energy vector thermal, electrical and cooling system in a simulated commercial building. The study shows significant cost savings when a Combined Cooling Heating and Power (CCHP) unit is managed by the proposed control system.

2.2.2 Operational HVAC Optimisation

Several studies within the literature focus on control of HVAC components given that this accounts for a significant proportion of energy demand in modern buildings. Often, this is achieved through control of heating and cooling set points throughout the day to allow potential pre-cooling or pre-heating solutions. Specifically, this sub-section will review studies that aim to control HVAC parameters at a short-term, operational level, typically with control horizons equal to, or less than, a day. This field has been revolutionised in recent years through the application of advanced computational intelligence techniques including meta-heuristic optimisation methods, machine learning prediction models, fuzzy logic and multi-agent approaches [131].

In [132], the authors' coupled an EnergyPlus simulation with a MATLAB, MPC procedure using the middleware software BCVTB (Building Controls Virtual Test Bed) which is designed to facilitate data exchange between EnergyPlus and other software such as MATLAB. The MPC scheme controlled the extent of the pre-cooling with the objective of minimising energy cost. The various potential solutions were assessed in EnergyPlus and compared to typical control strategies. However, the case study building was very simplistic due to the simulation time that would be required to simulate complex, realistic buildings. A 24-hour scheduler utilising EnergyPlus was developed in [70] with the aim of simultaneously controlling the thermal comfort, visual comfort and indoor air quality whilst minimising the energy consumption. It used a Genetic Algorithm (GA) which used an EnergyPlus model as the evaluation engine to control window blinds, ventilation, and window opening operation for just a single zone.

In both, [133] and [77], Ascione et al. developed a multi-objective GA optimisation procedure to control indoor set point temperatures using an EnergyPlus model to evaluate potential solutions. Both case studies have demonstrated significant potential energy savings, however, the case study building was relatively simple, containing just three zones. Using the EnergyPlus model as an evaluation engine led to a computational time of 90 minutes to develop an optimal schedule for the next 24-hours. Such a computational period would inhibit the use of sliding-window, MPC, which would have to re-optimise every hour.

In practice, using a detailed white box simulation in conjunction with an advanced metaheuristic optimisation strategy, such as a GA, is not possible in most scenarios targeting operational optimisation. This is due to the considerable number of evaluations required per iteration and the computational time required to complete an evaluation. The previously discussed works focus on very simple building energy models or just a single zone. To apply these methods to a realistically complex building would require significant computational power to reduce simulation times to acceptable limits (i.e. below 1 timestep). Thus, the focus must turn to creating surrogate, black or grey box, models which can accurately replicate the output of a white box model but can compute with minimal computation expense and time allowing their use in real time.

MPC using grey box modelling techniques were applied to a Czech university building in [134] and [135]. Blocks of the building were modelled using an RC model taking weather predictions as inputs. The optimisation was set up as a linear quadratic programming problem and the objective was to minimise energy consumption by controlling the supply water temperature set point. This strategy was implemented on the real building for over 2 months and was shown to reduce energy consumption by 15%-28%. Whilst this optimisation considers occupancy as a disturbance, it does not include predicted occupancy as a model input. Furthermore, only block level supply water temperature is controlled rather than the desired set point temperature in each zone. Karlsson and Hagentoft [136] aimed to control the flow rate of an underfloor heating system using an MPC strategy. The authors simultaneously developed a complex numerical model alongside a simplified RC model and found a good comparison between the two.

Oldewurtel et al. [137], adapted traditional MPC to Stochastic MPC. Essentially, this means the MPC strategy took into consideration uncertainties in forecasts when carrying out the optimisation. This resulted in a slightly more cautious optimisation that did not go so close to the comfort boundaries whilst still achieving good energy savings. Mahendra et al. [138], also aims to address the problems that stem from forecasting uncertainties produced by a

RC model. This solution runs a reactive algorithm in between the MPC time steps that can take swift action if the forecasts are clearly incorrect due to an unexpected spike in occupancy for example.

Molina et al. [139], produced an MPC strategy to control heating and cooling in a residential building using a state space model as an evaluation engine for a GA. However, this work considered unrealistically simplified ideal heating and cooling and the control strategy only considers a 1-hour prediction horizon which is not long enough to be able to effectively utilise pre-heating or pre-cooling. State space representations of the indoor temperature, lighting, humidity and CO_2 levels were used in [140] to develop improved system controllers to maintain closer adherence to set point values whilst using minimal energy consumption. The importance of considering occupancy and managing energy at a zone level is demonstrated in [141]. An Auto-regressive with exogenous input model (ARX) was used to model each zone. Disturbances including occupancy and future predicted heating output from adjacent zones was also included. A distributed MPC strategy was developed where each room has an independent controller that considers these disturbances. The controller produced a 13% reduction in energy consumption and a 36% improvement in thermal comfort. Erickson and Cerpa [142], also developed a HVAC control strategy based on occupancy. A Markov Chain occupancy model was developed to allow the building control strategy to take advantage of sporadically occupied zones to save up to 20% on an EnergyPlus, simulation-based, case study.

Use of black box building models is also common within the literature, for example, Papantoniou et al. [112], optimised the operation of fan coil units in a Greek hospital. An ANN predicted the outdoor temperature and the indoor temperature also taking the HVAC operation as an input. A genetic algorithm was used in conjunction with a fuzzy controller to minimise the cost of the energy consumption and ensure thermal comfort for the occupants. However, the optimisation time horizon was limited to only 8 hours. Lee et al. [113], used an ANN based MPC strategy to control a zone AHU. It aimed to calculate the optimal AHU cooling operation over the next 24 hours to minimise the energy cost and maintain thermal comfort using Mixed Integer Non-Linear Programming, MINLP. The ANN accurately predicted indoor temperature and energy consumption, but the application was limited to only a single zone within a building. An ANN based controller was also developed in [143]. The ANN predicted the change in indoor conditions including temperature, relative humidity and the PMV. These predictions are subsequently used to control heating, cooling, humidifying and dehumidifying devices to minimise over or undershoots often found in non-predictive, conventional control. Whilst this approach provided better thermal comfort compared to conventional controllers, it did not consider the minimisation of energy consumption as an objective in its control scheme.

Afram et al. [144], developed a new algorithm for training ANN which was applied to modelling several HVAC components. The ANN were integrated into a MPC platform to control the ventilation rate, buffer tank set point temperature and indoor set point temperature. The control scheme showed aptitude for reducing the energy costs of the house by shifting the load to cheaper time periods. However, the building only has one set point temperature rather than zone level set points and occupancy was not considered in the MPC formulation. An MPC strategy that controlled both humidity and indoor temperature to maintain a PMV constraint was demonstrated in [145]. ANN predictive models were combined with a branch and bound optimisation to achieve energy savings in the order of 30% compared to a baseline solution.

A multi-objective particle swarm optimisation (PSO) was developed in [146] to minimise the electricity cost of the HVAC system whilst maintaining thermal comfort for the occupants. The optimisation strategy considers a day ahead electricity pricing tariffs and outdoor temperature forecasts. The cost was reduced by 18.7% through pre-cooling in low price periods, however, both the thermal and comfort models used are overly simplistic. Namerikawa and Igari [147] conducted an MPC approach to the management of an air conditioning unit in a zone supplied by solar PV panels. The PV generation is predicted through regression from which the MPC aims to minimise peak load and cost to the consumer. These objectives were achieved somewhat, however, the thermal constraints were lax given an upper bound temperature of 30°C .

An explicit MPC to manage HVAC systems was outlined in [148] with the aim of controlling both indoor temperature and CO_2 levels. Using this method, the controller stores a bank of previous actions and depending on the scenario selects the best suited action. Whilst the authors argue this approach allows on-line optimisation with limited computational burden, however, this approach cannot think ‘outside the box’ to produce potentially more optimal solutions. An intelligent, rule based, decision support system was created in [149] to control indoor temperature, humidity, luminosity and air quality. It had a stored knowledge base and a wide array of sensors allowing it to choose the best course of action for the specific conditions. This led to a reduction in energy consumption of around 10% in a real trial. Integrated control of HVAC, lighting and shading was also considered in [150] using a dynamic programming approach. Due to the complexity of the problem and the coupling of separate systems, the problem was decomposed into several sub-problems to make the methodology scalable and tractable.

2.2.3 Long-Term Building Optimisation

Whilst the studies in the previous section aimed to achieve relatively short-term, operational optimisation of building HVAC systems, the papers cited in this section use longer term approaches. This may be targeted at the design phase, pre-retrofitting analysis or during the building operation. These sort of studies tend to produce one-off results that should be implemented consistently rather than being required to re-optimise every 24-hours. In many cases, the solutions provided by the studies in this section could be carried out in conjunction with the operational optimisation methodologies previously discussed in Section 2.2.2.

Due to the longer time frames considered in this section, the use of white-box simulation models in conjunction with meta-heuristic optimisation strategies is more viable as solution time is less critical. Papadopoulos and Azar [151] combined an EnergyPlus with a MATLAB multi-objective GA to minimise annual energy consumption, thermal discomfort and productivity loss by setting the heating and cooling set point temperature. However, the same set point temperatures were used throughout the entire year, failing to adjust to variable weather of occupancy conditions of each day.

Li et al. [152] addresses design stage optimisation in conjunction with an EnergyPlus model. The decision variables included the buildings' orientation, window transmittance and width with multiple objectives including lifetime cost, average PMV and CO_2 production. The study also trialled the use of a surrogate ANN model in the place of the EnergyPlus simulation model. This dramatically decreased the solution time but led to a slightly less optimal solution due to prediction errors. Further examples illustrating the use of surrogate models combined with optimisation can be found in both [153, 154]. A TRNSYS model was run several times to produce a representative bank of data from which an ANN was trained. The developed ANN accurately predicted annual energy consumption and thermal comfort within the building based on retrofit design decisions as inputs. The ANN was combined with a multi-objective GA to minimise energy consumption, discomfort and retrofit costs. Both studies showed the benefits of deploying an ANN as opposed to a white box simulation model as the evaluation engine due to the dramatic decrease in reported computational time. This type of scheme was further enhanced in [155] which developed generic ANN that accurately replicated entire classes of buildings (e.g. an office built from 1920-70) rather than just a single building. Once combined with an optimisation procedure, the methodology recommended the most cost-effective building retrofit measures depending on budget. Magalhães et al. [156] developed an ANN to forecast the annual energy consumption of a building based on readily available energy performance certificates, EPC, and specific user defined characteristics such as the length of the heating period and the percentage of area heated. The authors' argued that providing such information to occupants would allow more informed decisions in relation to energy saving measures.

Several longer-term building energy optimisation methods are based around studying historical data to learn unexpected trends. For example, the performance gap between design stage and reality was addressed in [157]. By effectively analysing the real-life occupancy patterns of an educational facility, some zones could be closed off for several additional hours to save an estimated 20%. Assessment of existing HVAC schedules and rules was conducted in both [158, 159] through creation of a validated simulation model. This facilitated the trialling of several alternative HVAC rules with an assessment on potential energy savings they may bring. This included determining the optimal start-up and turn-off times from HVAC components and selecting heating and cooling set-point temperatures to reduce energy demand. Similarly, [160] and [161] trial several heating and cooling strategies based on internal simplified models with the aim of finding the method which achieves the comfort conditions at minimal cost. Both studies consider options such as pre-cooling / pre-heating, cycling on/off during the day and turning off early to avoid high energy cost periods. However, this sort of study is limited as the optimal strategy is found based on a sample day and is based on a set of pre-defined options. It is unlikely that the optimal solution to the sample day is equally applicable to different days and weather conditions throughout the year.

2.2.4 The Application of Semantics

An additional emerging trend within the literature is the use of semantic web technologies. Essentially, semantic web technologies aim to ensure data interoperability, machine to machine communication, and to ascribe additional contextual information to data exchange. Several studies have been conducted to apply semantic web technologies to the built environment. A state-of-the-art review carried out by Abanda et al. [162] demonstrated that much of the existing work has aimed to develop ontologies relating built environment concepts and objects with a specific focus on the utilisation of BIM. An ontology is a semantic web concept that aims to develop a common vocabulary to describe concepts and objects through a unifying shared model [163]. Not only do they describe objects, they also describe the relationship between objects including rules and logic in order to build knowledge rather than just information [164].

At a building-level, the dominant form of digital BIM representation is through the Industrial Foundation Class (IFC) schema developed and maintained by the buildingSMART organisation[1]. Efforts continue to coalesce around a definitive ontology for describing the data contained within an IFC model towards an ifcOWL representation [165]. The semantic definition provided by ifcOWL, via BIM, could provide the basis for much improved life cycle management of buildings. It facilitates interoperability and the linking of data across domains such as BIM, infrastructure, and energy [166]. The open and shared central model can be supplemented by additional external data sources including IoT sensors, building management systems and energy networks mapped through upper level ontologies. Having a single, unifying model of a building can significantly aid facility managers through the operational phase as only one model will have to be updated and all other dependent modules will automatically understand the changed made. Curry et al. [167] agreed that BIM models can “serve as an information backbone” for more intelligent management platforms. The author went on to develop a cloud-based management platform by linking an ifcOWL model with BMS sensor data to provide inciteful feedback to occupants based on their energy consumption. Osello et al. [168] also utilised a BIM model generated in Autodesk Revit as the central model from which thermal and lighting specific modules could be produced in more specialist software (in this case TRNSYS and Radiance respectively).

An example of the use of IFCs and semantics can be found in [169]. In this study, a building ontology based on IFC was combined with a sensor ontology using an upper level mapping ontology. This was combined with a sensor network in an office zone measuring temperature, motion, and humidity. The paper argues that the combination of the ontology, sensors and intelligent agents can provide incitefull feedback to facility managers through inferences. The examples provided included the detection of periods when the zone was heated and lighting was on, yet the room was unoccupied. In addition, it aimed to determine occupant comfort preferences for finer control of heating and ventilation. Corry et al. [170] aimed to address the performance gap between building design and operation through a performance assessment ontology. This ontology mapped three existing ontologies, ifcOWL to describe the building, SimModel which captures building energy simulation concepts, and SSN

[1] https://www.buildingsmart.org/

which covers sensors and measurements. By linking actual measurements with energy simulation, the authors argued that facility managers could detect faults more easily and improve real building performance. A smart home management system deployed on a semantic base was envisaged in [171]. This study provided a semantic extension of the UPnP communication protocol and maps together several ontologies describing energy, context, the user, devices, and services.

To provide a stable platform from which a MAS smart home can be produced, Kofler et al. [172], developed an OWL ontology to capture and semantically link the core concepts within the smart home. These included aspects of the building, user information, processes, exterior information, energy and resource. Specifically, the authors focus on the source of the energy supply so any control platform built on top of the ontology could make intelligent decisions if the user wished to reduce their carbon footprint. Ruta et al. [173] also produces a semantically linked MAS control procedure. Building devices are represented by agents which are coordinated by a central agent. The control procedure must juggle the constraints of varying importance and when posed with an over-constrained problem, relax the least important constraint.

An example of utilising semantics for real-time building control and optimisation was demonstrated in the KnoholEM project [174]. This project extended an ontology based on IFCs to also include objects and concepts relating to energy consumption, management and sensing. This underpinning ontology enabled the system to interface with building energy management systems regardless of the communication protocols they used [175]. It also allowed connection to energy simulation models which could be run in near real-time to aid in fault detection and determination of building performance. The ontology ensured that objects such as zones, actuators and sensors modelled in the BIM, the energy model, and recorded by the BMS share common descriptions and are interpreted as representations of the same physical object by the system. The semantic base aided the generation of energy saving rules through surrogate ANN machine learning models based on energy simulation data and rules based on data mining of recorded historical data [176]. A GA then produced a set of optimal rules based on the desired energy saving requested by the facility manager. A fuzzy inference system selected the most appropriate rule to be suggested to the facility manager through a simple user interface. The semantic mapping enabled a 3D model of the building to be presented to the facility manager with the capability to select individual zones to retrieve a breakdown of performance in terms of energy consumption and comfort [177].

Whereas IFC is the leading modelling structure at a building level, CityGML

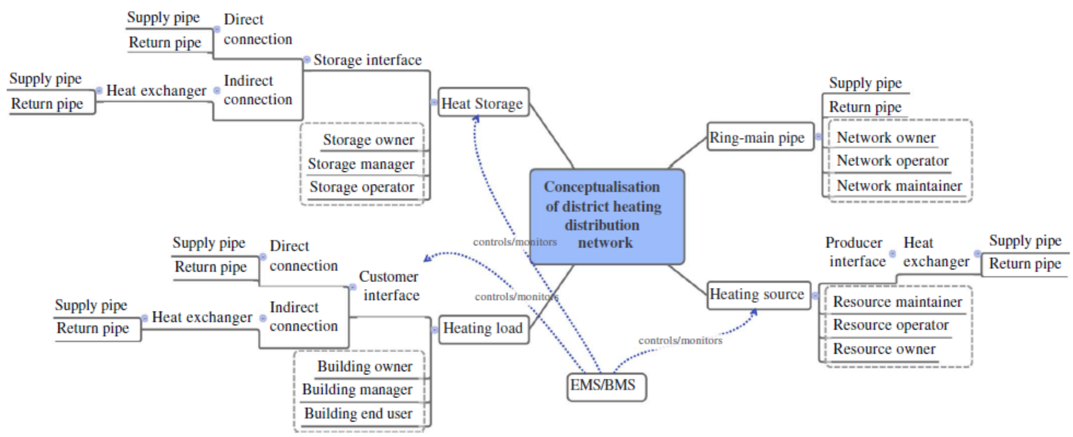


Figure 2.1: Conceptualisation of district heating networks, taken from [182]

is becoming the common information model to represent information for city scale modelling [178]. The Energy Atlas Berlin project used CityGML to semantically describe a neighbourhood in Berlin. CityGML enables the semantic decomposition of wall, ground and roof surfaces alongside additional contextual information such as the year of construction, building function, and weather information to be able to produce heating demand forecasting and solar PV availability at a building-level on a city-scale [179]. The SEMANCO project also developed an urban scale ontology which included similar building-level information but also aimed to describe the energy infrastructure and systems, mapping the energy end use to the energy sources and the energy carriers [180]. The ontology was then deployed to enable an integrated platform allowing city scale energy analysis to allow targetted interventions by urban planners. An effective link mapping between the building-level concepts provided in IFC and the district or city-level concepts provided by CityGML is required to manage energy in a more holistic manner [181]. One attempt to capture district-level energy concepts in an 'ee-district' ontology is provided in [182]. The ontology is mapped and integrated with existing upper level ontologies to build on accepted definitions of concepts and to allow interoperability at different scales. This ontology was validated through an instantiation based on a district heating case study in Ebbw Vale. The description and interconnection of various district heating concepts are shown in Figure 2.1, taken from this example. The author argues that knowledge captured in the ee-district ontology plays a key role in the delivery of a multi-agent semantic district optimisation.

2.2.5 Summary

The literature reviewed in this section shows the diversity of building optimisation strategies. There are several different objectives including minimisation of cost, energy consumption, peak load, and maximisation of thermal comfort. The decisions variables considered are also very broad; from household electrical appliances such as washing machines and fridges to HVAC components such as fans and air conditioning units, and beyond to control points such as set point temperatures. However, there are some common themes within the work reviewed in this section. These building-level studies overwhelmingly consider the control and shifting of energy demand whilst rarely considering the energy supply. Some studies do include some local renewable resources, in the form of solar PV, as well as energy storage capacity but that is the extent of energy supply consideration. A further theme in this section is the importance of dynamic or ToU tariffs [183]. With the deployment of smart meters, these are likely to become more widespread and have a significant impact on energy cost when included in many of the building control strategies discussed in this section. Regular consumers cannot be expected to understand and alter their demand patterns based on the forecast energy price each day. Therefore, automated control methods that are perceptive of user preferences are essential.

Regarding the modelling of building energy demand, all the techniques outlined in Section 2.1 have been used successfully within optimisation strategies. However, many of the grey box fail to consider external heat gain disturbances such as occupancy or resulting from the equipment that they use. For the effective deployment of a zone-level HVAC controller, these disturbances play a significant role and must be considered alongside real-time weather forecasts. The long term optimisation approaches reviewed in this section demonstrate the importance of reviewing operational energy consumption data to detect outdated or ill-conceived BMS rules. However, whilst these audits can prove effective, they cannot compete with the short-term operational optimisation strategies that take the exact conditions of each day and determine the best solution for that specific instances. Any new rules generated after an audit are highly unlikely to produce an optimal approach for all seasons and due to the constantly changing functions of buildings are likely to be out of date in the near future.

An additional factor that may feed into building energy optimisation is the deployment of semantic web principles. The use of semantics and ontologies help to overcome interoperability challenges often faced in older buildings. The many components within a building often communicate using different communication protocols. Several researchers have demonstrated that ontologies based around BIM and specifically IFC can allow clear and consistent definition of building objects and concepts and provide the ability to link with external

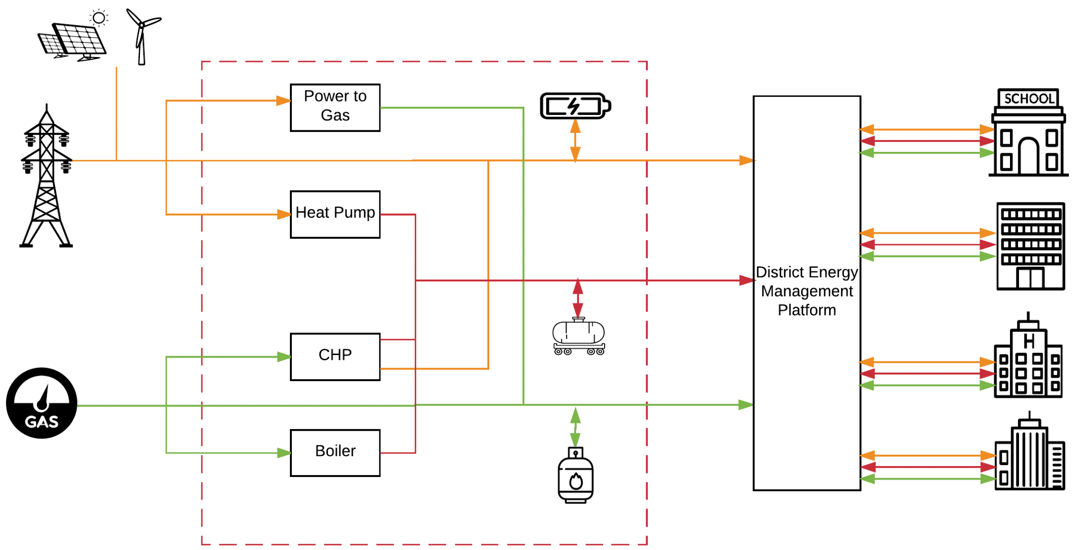


Figure 2.2: Schematic layout of a multi-vector energy hub. Yellow indicating electricity, red heat, and green gas.

factors such as energy prices, weather forecasts, energy simulations, and BMS data. It its core, semantic web technologies add context to data and objects. By making controllers more context-aware, they are able to make more informed and beneficial decisions for the user.

2.3 Modelling of a District Energy System

Section 2.1 and Section 2.2 both focus specifically on energy management at a building-level. Energy management at this level tends to focus on controlling and optimising energy demand. However, given the decentralisation of energy systems towards localised microgrids, it is imperative that district-level energy systems are also considered to achieve truly holistic energy management including the energy supply. Modelling and optimisation of entire district energy systems has already been attempted in several academic publications and scientific projects. The leading approach in the literature to achieve this is the Energy Hub modelling concept [184]; which simplifies complex urban energy systems to a series of input-output energy hubs. The inputs are in the form of primary energy sources, and the outputs are the produced electricity, heat and/or gas. The 'Hub' itself contains the mathematical modelling of the conversion process and technologies (Figure 2.2). However, this type of modelling often simplifies energy conversion units to simple constant efficiencies, failing to take into account part load characteristics, warming up periods and other energy losses.

The energy hub concept has been utilised in several papers studying the optimal layout and design of district energy systems [185–189]. This includes selection and sizing of the energy production units and consideration of which energy hubs should be connected. This work is aimed at the design stage or future scenario evaluation and is based on steady-state analysis of known (or assumed) peak demand. Therefore, the assessed temporal scale is years of assumed behaviour rather than day to day optimisation at a sub-hourly resolution.

Operational optimisation of energy hubs can also be found in the literature, often using MPC, [190–192]. In [193], the energy demand was determined from EnergyPlus building simulation models; then the potential, uncontrollable, renewable supply was assumed forecast and finally the energy hub then matched supply and demand in an optimal way using linear programming techniques. A dynamic particle swarm optimisation study was carried out on a Canadian case study in [194], using known hourly, heating, cooling, electricity and transportation loads. Maroufmashat et al. [195] also built on the energy hub concept to create a generic smart energy network model for operational optimisation. This paper includes detailed modelling of energy storage, which was included in the energy hub modelling.

Considering a network of energy hubs is shown in the literature to be an effective way of optimising energy management at a district level. However, all of the discussed studies made a number of simplifications. The buildings are often simplified models or using design stage assumptions rather than using accurately calibrated building energy models. The building energy demand is also assumed perfectly forecast and inflexible with no consideration of demand-side management or demand response measures. The efficiency of the energy conversion units is often oversimplified. They assume a thermal and/or electrical efficiency to be constant and therefore does not include part load factors and warming up characteristics, which are vital for a realistic day-ahead optimisation [196].

There is potential to improve upon the energy hub model with more detailed component models in place of a conversion matrix with static efficiencies [197]. These models could be mathematically derived or could use machine learning or artificial intelligence. The purpose of this section is to provide an overview of existing modelling techniques of components within urban and district energy systems including the emerging technology of power to gas. This section intends to provide a wider, holistic, summary of modelling a district energy system specifically for operational optimisation. It will discuss not only the well-known physics-based modelling software but also include newer computational intelligence and machine learning techniques for modelling individual components. Indeed, this section will devote an increased focus on these approaches as they are likely to be more suitable for real-time, operational optimisation but are largely neglected in existing urban energy modelling reviews.

2.3.1 Combined Heat and Power

Combined heat and power, CHP, is becoming a favoured technology during the transition from a fossil fuel energy infrastructure to a low carbon future. While they still frequently use fossil fuels, namely natural gas, they can achieve greatly improved efficiencies. This is as a result of utilising the heat by-product from electricity generation in a local heating system and thus also reducing transmission losses. Total efficiencies of around 80%-90% have been achieved as opposed to the 30%-40% figure achieved in traditional, large-scale, fossil fuel electrical power plants [198]. There is a range of CHP types based mainly on the type of prime mover, typical examples include internal combustion, fuel cell and Stirling engine. Furthermore, during summer the heat produced by the CHP can be used to drive cooling cycles forming trigeneration cycles (heating, cooling, and electricity). The main three cooling technologies driven by heat are absorption, adsorption and ejector cycles. An ejector cooling cycle, in particular, was modelled in [198], based on the heat from a CHP.

Best et al. [199], developed a district energy modelling tool with a modular design. In particular, the authors focused on the mathematical modelling of CHPs and chillers. The CHP model used manufacturers rated capacity and adjusts this for altitude, outdoor temperature, and part load ratio using statistical regression equations. The resulting model allowed the fuel consumption, cost, and CO2 emissions to be calculated based on the energy demand. Wang et al. [200], aimed to optimise the operation of several CHP units and thermal energy storage for a district heating network. Their CHP model was based on a convex, feasible operating region based on characteristic points. However, for 2 of the 3 CHPs included in the case study, they only had two characteristic points at maximum and minimum operation. The authors included ramp rate constraints, which were modelled as a percentage the CHP output can increase or decrease from one hour to the next. Maintenance periods were also considered in this optimisation problem.

Detailed thermodynamic modelling of micro-CHP, residential scale devices has been developed as part of an IEA project in [201] A grey box approach to modelling sub-components of 4 types of CHP has been taken. The model reflected partial physical processes but also required empirical constants to be determined based on the measurements obtained from real units. Each subcomponent within the device was modelled as a separate control volume to which fundamental conservation laws can be applied. These models had been integrated into four different modelling platforms, namely ESP-r, TRNSYS, EnergyPlus and IDA-ICE. Validation of these models was provided in [202], which showed excellent agreement between simulation and measurement of a Solid Oxide Fuel Cell (SOFC) CHP. Average errors of 1.2%, 8.3%, and 5.4% were reported for electrical, thermal and total efficiencies. For more information on the detail of the modelling techniques see [203] for internal combustion engine and Stirling engine CHP's and [204] for information on solid oxide fuel cell CHP's.

Savola and Keppo [205] aimed to generate multiple linear regression models to calculate the power production of several CHP at part loads. While CHP power output at high loads is almost linear, as the part load decreases the power decreases non-linearly due to a rapid decrease in turbine isentropic efficiency. Therefore, this work proposed multiple linear regression models depending on the part load factor of the CHP. These can be described mathematically using the following equation:

$$P(Q, T_h, T_c) = a \cdot Q + b \cdot T_h + c \cdot T_c + d \tag{2.1}$$

Where P is power production (W), Q is the part load factor (-), T_h is the outgoing fluid temperature (°C), T_c is the incoming fluid temperature (°C) and a, b, c and d are regression coefficients. Using three separate regression lines for different sections of the part load curve was shown to be accurate versus a simulation model and yet remains a linear equation simple enough to be included in optimisation strategies.

An analytical approach to assess the characteristics of a cogeneration gas turbine unit was carried out in [206]. Using this approach, curves relating several parameter ratios (such as thermal efficiency over design thermal efficiency) could be related to the part load ratio. This work amongst others, is used in [207] to create best-fit curves to calculate part load thermal efficiency and part load fuel consumption as a function of the part load percentage. These curves were compared to experimental data of three gas turbine CHPs and showed excellent consistency. The equation for this curve is given in (2.2).

$$\frac{\eta_{th,PL}}{\eta_{th,Nom}} = -0.0000634(PL)^2 + 0.0137(PL) + 0.262 \tag{2.2}$$

Where $\eta_{th,PL}$ is the part load thermal efficiency, $\eta_{th,Nom}$ is the nominal thermal efficiency, and PL is the part load percentage where all variables are dimensionless.

Based on the reviewed literature, for wider district energy optimisation, multiple linear regression equations or non-linear regression curves are best suited for real-time operational optimisation and management. They provide an accurate representation of the behaviour of a CHP while requiring minimal computational effort to calculate due to their relative simplicity. This approach provides more realistic modelling than the constant efficiencies used in the state-of-the-art energy hub formulations.

2.3.2 Boilers

Typically, district heating plant rooms are comprised of multiple energy conversion technologies. Due to the decrease in efficiency in part load conditions and fluctuating electricity demand, CHPs are often sized to provide the baseload and operate continuously where possible. Additional heating load flexibility will be provided by more traditional boilers, which can more ably modulate their output based on instantaneous demand. Typically, these boilers will have very high thermal efficiencies and have a wider operating range than the more inflexible CHPs. The most commonly found fuel source for district-level boilers is natural gas however biomass is becoming increasingly popular due to governmental policy schemes.

A thermodynamically derived, mathematical model of a steam boiler was presented in [208] The model included factors for various sources of energy loss such as heat losses to the environment through each component and combustion losses. This allowed each source of energy loss to be analysed and potentially reduced. From the mathematical model, a part load efficiency curve was produced consisting of three distinct zones. From 0-40% load, a hyperbolic relationship between load and efficiency existed, from 40-80% there was a near linear relationship and above 80% resulted in near constant efficiency. The model was verified through comparison with experimental measurements. A similar method of model development was applied to domestic condensing boilers in [209]. The resulting model calculated outlet water and gas temperatures and thermal efficiency based on the inlet temperatures, flow rates and static boiler parameters. Petrocelli and Lezzi [210] analytically modelled a wood pellet boiler and analysed the effect of storage tank size and control strategy on the boiler emissions. The authors found that increasing the size of the storage tank decreased emissions due to less frequent startup and shut down times.

A numerical Computational Fluid Dynamics (CFD), software, ANSYS Fluent, was used to provide a more complete analysis of boiler behaviour in [211]. The verified model allowed analysis of flow conditions and flame behaviour as well as NO_x output. As a result, NO_x reduction strategies could be trialled before implementation. However, this level of detail does come at the cost of computational complexity as the model contains 6.8 million meshing cells which leads to a significant computational time. Similar CFD analysis of a biomass boiler was carried out in [212]. This study combined a detailed 1D model of the fuel bed to provide inputs to a full 3D CFD simulation of the whole boiler.

A simplified grey box model was derived in [213]. The authors aimed to make a generic boiler model consisting of three phases; the combustion chamber, heat exchanger and thermal storage. Where possible empirical relationships were used to ensure the resulting model required as few input parameters as possible, most of which can be found on standard boiler specification sheets. A generic boiler simulation model was also developed in [214]. Several different combustibles including oil, gas, pellet and wood chips were modelled and several flue gas temperature modelling techniques were used. The model was developed to be integrated into the TRNSYS simulation platform and claims a thermal efficiency prediction accuracy of $\pm$ 1%.

A combined, hybrid model for determining the behaviour of a large coal-fired, steam boiler can be found in [215]. A neural network was used to provide a simple calculation of flue gas temperature which was an input for an analytical model to calculate the thermal efficiency. The resulting model was therefore computationally simple enough to be used for real-time control applications. A simplified, non-linear, 3rd order state space model of a biomass boiler was used in [216] for a model based control application. The model-based control contributed a significant reduction in CO and particulate emissions and resulted in an improved thermal efficiency.

This section has shown several detailed, numerical modelling studies of the behaviour of boilers under various conditions and using various combustibles. However, for the purposes of real-time, operational control of a district, this level of computational complexity and simulation time is infeasible and unnecessary. Many of the modelling procedures described in this section are based on specific types of boilers. Therefore, in the authors' opinion, appropriate modelling of a boiler in a district configuration can be achieved through experimentally finding the empirical relationship between fuel input or part load factor and the heat power output similar to that found in Section 2.3.1. Efforts should be made to account for start-up and shut-down periods which can display distinct behaviour and are likely to effect real-time optimisation strategies.

Table 2.2: Summary of CHP and boiler modelling

Ref	Method	Input Parameters	Output Parameters	Model Accuracy	Component
[199]	Regression	Ambient Temp, Altitude, Part Load	Efficiency	-	CHP
[200]	Convex Operating Regions	Operating Point	Power, Heat and Cost Output	-	CHP
[201, 202]	Grey Box Modelling	Empirical Coefficients, Operating Strategy	Electrical, Thermal and Overall Efficiency	1.2%, 8.5%, 5.3% Average Error	CHP
[203]	Grey Box Modelling	Empirical Coefficients, Control Signal	Fuel Flow Rate, Electrical Output, Heat Recovery Rate, Outlet Temp	R^2 = 1, 0.993, 0.991, 0.991	CHP
[205]	Multiple Linear Regression	Part Load, Output Temp	Power Production	<0.01 Squared Error	CHP
[207]	Regression	Part Load	Relative Efficiency	-	CHP
[208]	Thermodynamic Principles	Boiler Static Data, Operating Strategy	Thermal Efficiency	0.35% Mean Error	Gas Boiler
[209]	Thermodynamic Principles	Boiler Static Data, Ambient Conditions, Fuel and Water Mass Flow Rate, Water Temp	Outlet Water and Gas Temp, Heat Output, Efficiency	0.2-2.5% Relative Error (Efficiency)	Gas Boiler
[211]	CFD	Geometry, Boundary Conditions, Operating Strategy	NO_x Emissions, Boiler Temps, Flow Velocities	<16% (NO_x)	Biogas Boiler
[213]	Grey box Modelling	Empirical Coefficients, Static Manufacturer Data, Operating Strategy	Hot Water Supply Temp, Flue Gas Temp	<1% to <8% Relative Error	Gas Boiler
[215]	ANN + Analytical Model	Feed Water Temp, Oxygen Content, Thermal Power, Heat Flux to Preheater, Air Temp, Fuel Lower Heat Value	Flue Gas Temp	R^2 = 95%	Coal-Fired Steam Boiler
[216]	State Space Model	Biomass Flow Rate, Primary Air Mass Flow, Sum of Primary and Secondary Air Mass	Residual Oxygen Content, Feed Temp	-	Biomass Boiler

2.3.3 Solar Energy

Power systems operation and planning is being performed according to the smart grid vision [217]. With more renewable technologies being integrated into existing and new energy supply infrastructure, especially the non predictable ones (wind and solar), it would be challenging to maintain balance between supply and demand. A continuous balance always needs to be maintained between supply and demand at any moment by continuously controlling demand and adjusting energy generation [218]. The stochastic nature of solar energy generation introduces exigent issues for the optimal operation and planning of smart grid. Predictive analytics will play a significant role towards optimal real-time management, secure operation and maintaining a balance between energy supply and demand. Solar energy generation is dependent on several factors such as orientation, shading, cloud cover, air temperature and solar irradiation. Therefore, prediction of solar energy output is often dependent on the prediction or measurement of these parameters. Whilst the field of solar energy systems is expanding to include building integrated solar systems this review will only consider the most common and developed solar energy technologies namely photovoltaic panels and solar thermal collectors.

2.3.3.1 Photovoltaics (PV)

The textbook approach to calculating the electrical power generated by a solar cell is defined as:

$$P = I \cdot \eta \cdot A \tag{2.3}$$

Where P is the power produced (W), I is the total solar radiation on the PV surface (W/m^2), η is the total system efficiency (-), and A is the area of the PV panel (m^2). However, making this calculation is dependent on knowledge of potentially difficult to obtain parameters such as solar radiation, shading, ambient temperature and solar cell efficiency which may not be constant. Durisch et al. [219], emphasised the need for more detailed information than that provided by a manufacturer datasheet at standard test conditions. It empirically modelled PV efficiency as a function of solar cell temperature, global irradiation and relative air mass. From ambient temperature and global radiation forecasting the cell temperature was determined through an empirical relationship. Then the cell efficiency was calculated using a further empirical relationship and hence cell power output could be produced using equation (2.3). The authors argued that their PV efficiency model could aid planners when selecting the type of PV cell to deploy in different regions based on typical ambient temperature and global irradiance. However, they did not foresee the model being used for short term power prediction. The developed model has been further validated in both [220, 221], where the model was adapted and applied to real test sites in Algeria and Bulgaria respectively to assess the performance under different operating conditions. Additional development and refinement of the Durisch model was conducted in [222] by including wind speed as an input. This produced an alternate method of calculating PV cell temperature, as a function of ambient temperature, global irradiance and wind speed, which then impacted the resulting estimate of cell efficiency. A more simplified model was produced in [223] which does not require a large number of input parameters. However, due to its simplified nature, the model outputted the daily energy performance of a PV solar cell which is not suitable for use in operational control.

PV panels can also be modelled using a simple electrical circuit composed of a current generator wired in parallel with one or several diodes and resistors. Ma et al. [224] reviewed the various configurations found in the literature. Modelling an ideal solar PV cell consists of just a single diode although this lacks accuracy due to its simplicity. Introducing the additional resistors and diodes, shown in Figure 2.3, increases the accuracy of the PV model but also increases the complexity and hence computation time. The most commonly used model is the 5-parameter model with 1 diode and 2 resistors as shown in Figure 2.3. However, this requires calibration procedures to determine the 5 parameters. Examples of procedures to determine the 5 parameters can be found in [224–226] along with validation of the models against measured performance. The modelling of PV arrays under partial shading was presented in [227]. The model's inputs are the PV panel's characteristics (maximum power, current, and voltage at the maximum power point, short circuit current, open circuit voltage) the shading patterns, solar insulation level, number of modules, working temperature and number of blocking diodes. The output of the simulation was the I-V characteristic and the maximum power point for each group of the PV panel. Despite the high accuracy of these models they still require weather parameters to be measured or predicted as inputs which can be difficult in practice.

Whilst solar cell equivalent circuits are the most common approach to modelling solar PV power output, advances in artificial intelligence and machine learning are beginning to emerge as contenders. A rural PV-Diesel hybrid system was modelled and optimised using neural networks in [228]. An ANN was developed to predict solar radiation based on more commonly available weather data. This was then used as an input to another ANN to predict the power output from a PV array. Using this information, optimal dispatch of solar

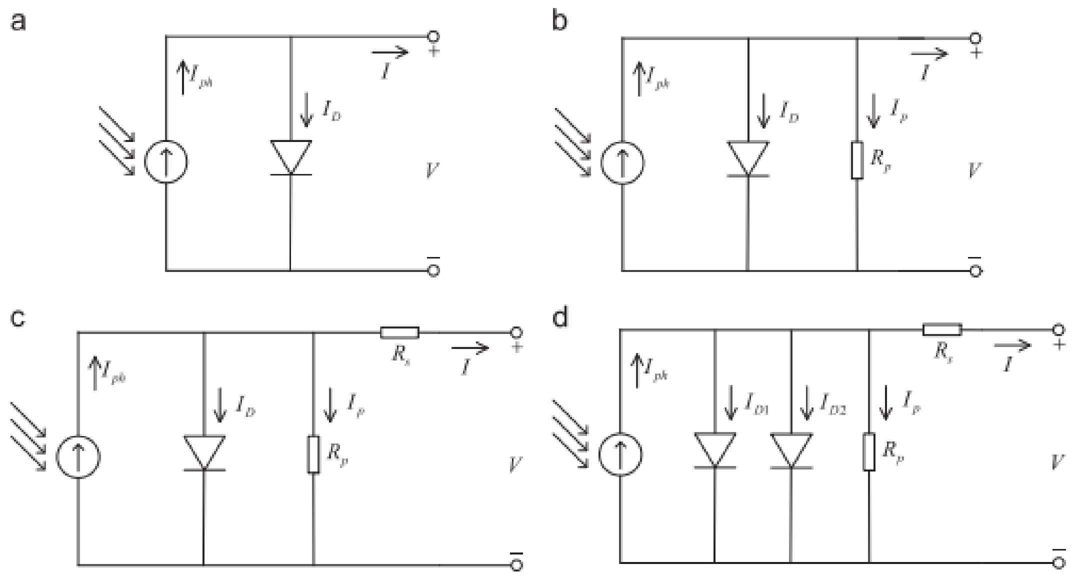


Figure 2.3: Solar cell equivalent circuits. Source: Ma et al. [224]

power and diesel generator operation could be found. Kharb et al. [229] uses an ANFIS model to improve the efficiency of a solar panel by maximum power point tracking, MPPT. They use temperature and irradiance as inputs and from this predict the MPP which allowed the controller to react quickly to changing environmental conditions.

As equation (2.3) demonstrates, solar irradiance is directly proportional to the power output of a PV cell. Therefore, prediction of solar irradiance and solar power output are almost one and the same. Three different types of ANN model were trialled in [230] to forecast ground level solar insulation and ambient temperature which were then used to calculate PV panel power output. The models were trained using the previous 16 days meteorological data. The inputs to the model included the previous 24 hours insulation, temperature and atmospheric insulation as well as forecast atmospheric insulation and relative humidity. There was a small difference between the three types of ANN, each using different learning algorithms, and this was likely to be influenced by the ANN parameter values. The mean absolute percentage error comparing the model output and actual values was around 15-20% throughout the year which translated to a similar accuracy in predicting the power output. Similarly, [231], developed and ANN-based, 24 hour ahead, solar irradiance prediction method. Inputs to the model included mean irradiance value, air temperature and day of the month and very good prediction accuracy was achieved, particularly on sunny days. Day-ahead solar irradiance predictions were then used to calculate predicted solar power output, and this was compared to a real facility in Italy. An R^2 value of 0.9 and a mean absolute error of less than 5% was achieved. Deep learning techniques were applied to model the power generation of 21 different solar farms in Germany in [232]. Techniques trialled include Long Short-Term Memory (LSTM), Deep Belief Network (DBN) and Auto-Encoder LSTM. These were compared to a physical modelling approach as well as a ‘shallow’ Multi-Layer Perceptron (MLP) model. It was shown that whilst all machine learning models significantly outperformed the physical model, the deep learning methods only provided a small improvement over the MLP.

2.3.3.2 Solar Thermal

Whilst PV technology uses solar energy to generate electricity; solar thermal collectors aim to convert the same solar energy into useful heat often in combination with a hot water storage tank. Theoretical solutions and standards for calculating the efficiency and useful heat energy conversion of solar thermal collectors are widely available and were well explained in [233]. The analytical modelling of solar thermal collectors has been adapted to be included in building simulation platforms such as EnergyPlus and TRNSYS. However, this requires knowledge of several solar collector parameters in addition to many weather variables such as the solar irradiance, wind speed and ambient temperature. Therefore, like the case of solar PV, simplified models are required for wider scale, real-time, energy optimisation.

Several thermodynamically derived, mathematical modelling studies of solar thermal collectors can be found in the literature. These tend to develop models for improvements or alterations to the standard flat plate solar collector. For instance, [234] developed a model for a polymer air collector with an aerogel insulation layer. A model to calculate the efficiency, output temperature and component temperature of a novel counter flow v-groove solar collector can be found in [235]. Luo et al. [236] modelled the effect of using nanofluids to improve the system efficiencies of a solar thermal collector. Electrical circuit analogies can also be used for the modelling of solar thermal collectors as demonstrated in [237, 238]. Electrical circuit models simplify the mathematics of modelling solar thermal systems but still retain some knowledge of the physical components.

When sufficient amounts of data are available, it is possible to model solar thermal collectors using machine learning techniques, similar to the case of solar PV. For instance, the performance of a solar thermal system has been modelled using both ANFIS and ANN in [239] with comparable results. The model showed a mean relative error of 1% when predicting the stratification temperature, and 9% for the solar fraction. The results show a high level of accuracy and reliability using artificial intelligence methods, with a significant reduction in complexity compared to a full mathematical description of the system. However, the amount of data required (panel's characteristic, orientation, tilt, and solar radiation every minute) can be difficult to collect in practice. Kalogirou et al. [240], also used an ANN to predict the output characteristics of a large-scale solar thermal system. It predicted the energy output and the storage tank temperature with accuracies of $R^2 > 0.95$. However, this study focussed on the total daily energy output rather than the finer timescales required for operational optimisation.

2.3.3.3 Discussion

Section 2.3.3 has shown several mathematical and machine learning methods for predicting solar energy output. In the case of solar PV, the more simplified analytical models based on empirical relationships or equivalent electrical circuits may be suitable for use in operational control and optimisation due to their short calculation time. The analytical approaches used for solar thermal modelling are too complex for use in real-time optimisation. Accurate predictions of solar PV or solar thermal output will undoubtedly require relevant weather variables as inputs. Therefore, to predict future solar energy generation, accurate weather forecasts are required. In many cases, sufficiently accurate forecasts of variables on an appropriate temporal scale such as ambient outdoor temperature and relative humidity will be available from national meteorological services. The forecasting of global solar radiation has a higher associated uncertainty and is less commonly available publicly. Therefore, many of the machine learning methods reviewed in this section first aimed to predict solar irradiance and from that calculate the solar power output, offering a computationally efficient and simple approach. However, the common downsides associated with machine learning prediction models also apply for solar energy modelling. These include the requirement for a large amount of historical or simulated data and the inflexibility of the model to adapt to any changes made to the system. Furthermore, machine learning approaches can be susceptible to problems of overfitting. This occurs during the training process if the model fits too well to the training data set without learning the general trends. Then when applied to an unseen testing data set, the model performs poorly. Depending on the machine learning approach, different methods exits to prevent this. These include 'pruning' the trained model to remove any unnecessary links or stopping training early based on the performance of a validation dataset. Note that these drawbacks associated with machine learning are true of every application rather than just the reviewed studies presented here.

Table 2.3: Summary of solar energy modelling

Ref	Method	Input Parameters	Output Parameters	Model Accuracy	Location
[219]	Empirical Modelling	Empirical constants, Global radiation, Cell temperature, Relative air mass	Cell efficiency, Power output	-	Jordan
[223]	Empirical Modelling	Daily aggregate of module temperature, air mass, global radiation	Daily performance ratio	1.55-4.19% Relative RMSE	Switzerland
[224]	5 Parameter Model	Solar Radiation, Module Temp, Ambient Temp	Output Current and Voltage	<1.4% Relative Error	Hong Kong
[225]	5 Parameter Model	Solar Radiation, Module Temp	Output Current, Voltage and Power	<10% Relative Error	China
[228]	ANN	Date / Time, Wind Speed, Rainfall, Ambient Temp, Humidity	Solar Irradiation	MSE = 200 W/m^2	Australia
[229]	ANFIS	Solar Irradiance, Ambient Temp	MPP	-	-
[230]	ANN	Previous Solar Insulation, Temp, Atmospheric Insulation, Forecast Solar Insulation, and Relative Humidity	Ground Level Solar Insulation	MAPE = 15-20%	Japan
[231]	ANN	Ambient Temp and Solar Irradiance	Solar Power	r = 98.5-99.2%, MBE = 3.1-5.4%	Italy
[234]	Thermodynamic Principles	Thermodynamic Parameters, Weather Conditions, Inlet Temp	Solar Thermal Outlet Temp	-	UK
[235]	Thermodynamic Principles	Thermodynamic Parameters, Weather Conditions	Component Temps, Air Temp, Efficiency	<7% Relative Error	-
[237]	2D Finite Difference Thermal Model	Thermodynamic Parameters, Weather Conditions	Component Temp	5-10% Relative RMSE	France
[239]	ANFIS	Ambient Temp, Solar Radiation, Previous Tank Temp	Tank Temp, Heat Input, Solar Fraction	1-9% Relative Error	Canada
[240]	ANN	Average Daily Temp, Total Daily Solar Radiation, Starting Tank Temp	Daily Energy Output, Final Tank Temp	r = 95-96%	-

Note - MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Squared Error), MSE (Mean Squared Error), ANFIS (Adaptive Neuro-Fuzzy Inference System), MPP (Max Power Point), MBE (Mean Bias Error), MLP (Multi-Layer Perceptron), LSTM (Long Short-Term Memory), DBN (Deep Belief Network).

2.3.4 Wind Power

Wind power generation relies on wind speed, which could be influenced by obstacle, terrain and height. Wind power generation is stochastic in nature, and therefore the reliability of wind power generation is not satisfactory as it cannot produce and supply steady electricity to the electrical grid. The wind power penetration influences the power system operation. To tackle this challenge, the power system operators/decision makers must make a detailed schedule plan and set a reserve capacity for it [241]. Wind power may not frequently be considered a small-scale urban energy source as wind farms are often built on a large scale and in more remote locations. However, it is feasible that a wind farm may be first directly connected to an urban microgrid rather than the wider national grid. Also, given that wind power is one of the largest renewable generation sources currently deployed the author believes that prediction of this power generation is worthy of discussion. Two recent reviews [218, 241], state that there are three broad methods for calculating wind speed or wind power generation. These include physical-based, white box, numerical models, more traditional statistical models such as ARIMA, and newer artificial intelligence-based models such as ANN, fuzzy logic and Support Vector Machine, SVM.

Typically, the power generated by a wind turbine can be defined as a function of wind speed. However, a wind turbine will have four operational zones which should be defined by the manufacturer of the turbine. Initially, at low wind speeds the turbine will remain stationary and produce no power until a cut in speed is reached. Then in the second zone, the output power is a cubic function of wind speed (shown in eq. (2.4)) until the rated wind speed and power is reached. Where P, is the generated power (W), C_p, is the dimensionless power coefficient of the turbine, ρ, is the density of air (kg/m^3), A is the swept area of the turbine (m^2) and U is the wind velocity (m/s).

$$P = C_p \frac{1}{2} \rho A U^3 \tag{2.4}$$

In the third zone, the power output will remain constant at the rated power regardless of wind speed. Finally, if the wind speed becomes too high, the turbine will shut down to prevent damaging loads. A typical wind power - wind speed curve is shown in Figure 2.4. Therefore, the challenge of predicting wind speed and wind power are almost one and the same. However, the cubic relationship between wind speed and wind power exacerbates the error in wind power forecasting.

Whilst the wind-power curve is typically provided by manufacturers, this relationship does not factor in the specific context of each site (e.g. turbulence)

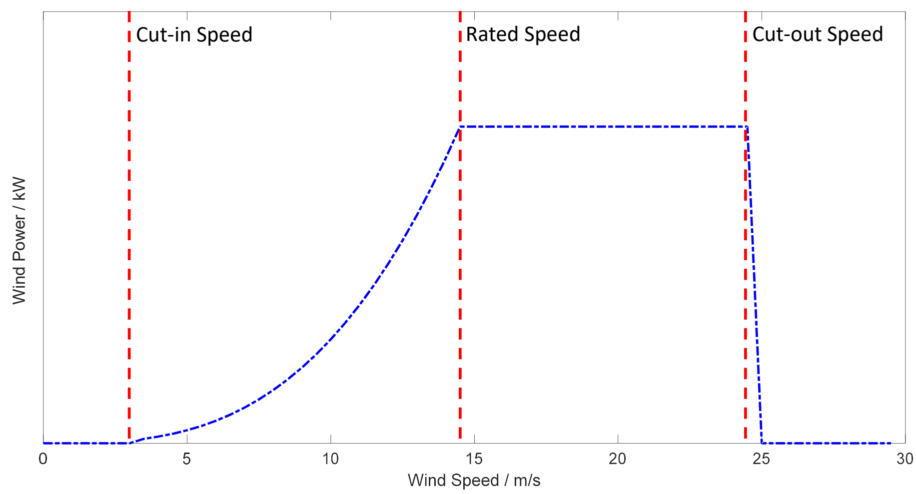


Figure 2.4: Typical wind power curve

or the condition of the turbine (e.g. deterioration and wear) or the proximity to additional turbines [242]. A common method found within the literature aims to develop site specific wind-power curves to achieve greater accuracy. Jin and Tian [243], proposed a probabilistic method to model wind power generation by adding a term to equation (eq. (2.4)) to reflect the stochasticity of the wind speed and power variation between wind turbines in the same wind farm. Lydia et al. [244], applied a range of techniques to generate a more accurate wind-power curve applied to 5 different datasets. These techniques included parametric modelling such as linearized segmented model, four and five parameter logistic expressions as well as non-parametric modelling including neural networks, fuzzy clustering and data mining approaches. For the sake of brevity only the results from the best model (5-parameter logistic function) and for dataset 1 are included in Table 2.4. Wind-power curve techniques may be necessary to understand more realistic site-specific conditions; however, the resulting curve still requires forecast wind speed as an input to predict power generation. Given that both recent reviews, [218, 241], state that for short-term prediction (hourly to sub-hourly) artificial intelligence based models are most effective, the rest of this section will focus on this area.

Five different machine learning techniques were applied to the prediction of future wind speed and wind power generation in [245]. They considered predictions using different time steps and prediction horizons. For very short-term wind speed and power predictions, they found SVM models outperformed other data mining techniques. This used the previous hours' time series data to predict up to an hour ahead in 10-minute intervals. The authors also considered a slightly longer timeframe for predicting wind power up to 4 hours ahead using the previous 4 hours, mean power generation data. Multi-layer perceptron, MLP, was the most accurate method for this timeframe prediction. An ANN was used in [246] to make short-term forecasts of wind speed at a wind farm site in Mexico. The ANN was trained based on time series data and used the previous hours values of wind speed to predict the next hour. A method combining wavelet transformation and neural networks to predict short-term wind power generation at a national level in Portugal was developed in [247]. Adding the wavelet transformation to get a better representation of the input data provided an increase in accuracy compared to using an ANN alone in all four seasons.

Quan et al. [248], aimed to address the calculation of prediction uncertainties. They produced an ANN that outputted the lower and upper bound of electrical load and wind power generation rather than a specific prediction value. A Particle Swarm Optimisation (PSO) procedure was used to minimise the width between these bounds under the constraint of 90% prediction coverage. The proposed procedure provided a significant improvement over more traditional methods although the width between the bounds for wind power generation remained high due to the randomness and intermittent nature of wind power. Similarly, [249] developed an ensemble mixture density neural network method to make a probabilistic forecast of wind speed and power. It provided not only a prediction but also confidence bounds for the predicted time series. It was found to outperform several other prediction methods regarding prediction accuracy and quality of the confidence bounds. An ensemble approach combined with wavelet transformation and a deep learning, Convolutional Neural Network (CNN) was proposed in [250]. The model required only recorded, time-series values of wind power as an input, from which it predicted wind power from 15 minutes to 8 hours ahead. The proposed methodology was compared to a back-propagation and SVM approach and was shown to outperform these models in every test. Welch et al. [251], developed three neural networks using different methods to predict short-term wind speeds. The authors found that recurrent neural networks outperformed the multi-layer perceptron architecture. An alternative, Naive Bayes decision tree prediction model is used in [252]. It aims to extract relationships between wind speed and additional weather data. Support Vector Machine (SVM) prediction models have been compared to ANN in [253] to predict mean daily wind speed. They find that the SVM model compares favourably against the ANN.

In summary, from the assessed literature, machine learning methods have the potential to provide the simplest and most accurate short-term prediction (up to 24 hours ahead) of wind power generation. However, in comparison to the other generation technologies considered in this section, wind power gen-

Table 2.4: Wind modelling literature summary

Ref	Method	Input Parameters	Output Parameters	Model Accuracy	Location
[244]	Parametric Modelling	Wind Speed	Wind Power	RMSE = 0.6408, MBE = 0.4874	Various
[245]	SVM, MLP, Decision Tree	Previous Wind Speeds	Wind Speed and Power	Relative Error = 15% and 23%	-
[246]	ANN	Previous Wind Speeds	Wind Speed	MSE = 0.0016, MAE=00399	Mexico
[249]	Ensemble MDN	Forecast Wind Speed	Wind Speed and Power and Uncertainty	RMSE = 1.9688 and 174.38	Taiwan
[250]	CNN	Previous Wind Power	Wind Power	CRPS = 0.281-4.339	China
[251]	MLP, RNN, SRN	Current Wind speed, Air Temp, Humidity	Wind Speed	Relative Error: MLP=0.5038, RNN=0.4354, SRN=0.4544	USA
[252]	Decision trees	Time, Atmospheric Pressure, Sea-Level Pressure, Temp, Humidity, Wind Speed and Direction, Insulation	Wind speed	Classification Error Rate = 17.54- 22.61	Japan
[253]	SVM and ANN	Previous Hours Wind Speed	Wind speed	MSE=0.0090 (ANN), MSE=0.0078 (SVM)	Saudi Arabia

Note - MLP (Multi-Layer Perceptron), RNN (Recurrent Neural Network), SRN (Simultaneous Recurrent Neural Network), MDN (Mixture Density Network), MSE (Mean Squared Error), MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), CNN (Convolutional Neural Network), CRPS (Continuous Ranking Probability Score) eration forecasting appears to be the most difficult. This is due to the almost complete randomness in the wind speed profile. In comparison to solar energy prediction, which is also weather dependent, the daily, or seasonal patterns are very limited. This is reflected in the wide uncertainties reported from the reviewed literature.

2.3.5 Power to Gas

The use of Power-to-Gas (P2G) (hydrogen or methane) technology is a relatively new concept for national energy systems. Due to plans for large expansions in stochastic renewable power generation, a technology is required to be able to effectively store or convert excess electricity at times when it cannot be dispatched. The P2G technology can convert excess electricity into hydrogen, and subsequently, methane for later use. These gases could be integrated with other sectors such as the chemical industry or transportation if hydrogen powered vehicles have significant take-up. Alternatively, methane (or synthetic natural gas) could be directly injected into the existing gas network with some researchers also suggesting that pure hydrogen could be injected to the same network up to a defined threshold with minimal negative consequences. If appropriate economic and technological conditions prevail, P2G could become a significant technology in the context of multi-vector energy systems as they have consequences for electricity, gas and heat as shown in Figure 2.5.

Both [254, 255] provide a technical overview of the systems and economic analysis. Initially, hydrogen is produced using water electrolysis requiring electricity as an input using one of three current methods; alkaline water electrolysis, proton exchange membrane electrolysis or high-temperature water electrolysis. Then a methanation stage converts the hydrogen to methane requiring a carbon source which could come from carbon capture at fossil fuel power plants, anaerobic digestion of biomass, or from the air. Whilst the technology is still largely at a pilot testing stage there is some concern at the high capital costs and relatively low conversion efficiencies of the technology.

Several national-level investigations into the economic feasibility of P2G have been carried out. Studies by [256, 257] modelled the integration of hydrogen electrolysers and P2G at a national level based on UK gas and electricity networks. For a future scenario with high wind power generation capacity, the authors found that allowing hydrogen to be directly injected into the gas network could reduce costs and emissions due to the greater capture of wind resource. A similar national scale, energy storage study in a Dutch context was considered in [258]. A comparison of pumped hydro, compressed air, and

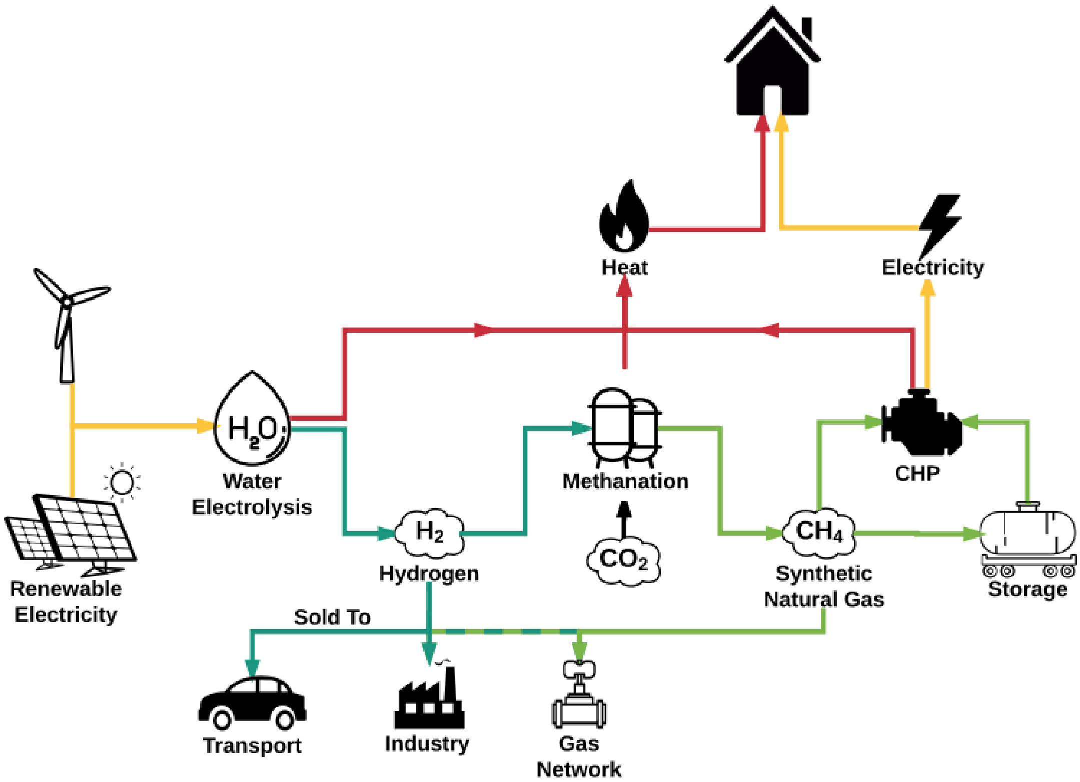


Figure 2.5: Schematic overview of the energy vector pathways of power-to-gas

power to gas energy storage was provided with varying capacity and different scenarios of wind power production. The study finds P2G to be the least cost-effective energy storage option due to relatively low cycle efficiencies. A future German scenario with 85% renewable energy was studied in [259]. This work aimed to consider the optimal amount of P2G capacity to deploy but also where to deploy it. In this scenario, P2G could lead to significant cost reductions, increased renewable share, and a reduction in CO_2 emissions. Guandalini et al. [260], analysed the effect of adding hydrogen electrolysers and gas turbines to large wind farms to provide balancing services. Including these units allowed a more 'aggressive' declaration of production to the transmission system operator as inaccurate predictions could be mitigated. An economic analysis of the use of P2G was applied in a German context in [261]. This work found that for the current and near future energy landscape, P2G is not a profitable method of providing balancing services to the national grid. This is due to high capital costs and relatively low gas prices in relation to electricity prices.

All previously discussed studies model the electrolysers or power to gas systems as a constant efficiency and were interested in long-term economic effects over a large geographic scale. Thermodynamic analysis of electrolysers and power to gas plants was conducted in [262, 263]. These studies assessed the energy demand for producing hydrogen at different pressures using different electrolysis pathways. However, these models were highly complex and would be problematic to integrate into real-time, operational, district optimisation. Despite their aims to account for thermodynamic irreversibility, these models have yet to be validated against real experimental data. Due to the fact that P2G technology is relatively new and still in an R&D phase, operational data is not widely available. This means that short-term, simplified, modelling of part load efficiencies is not covered in the state of the art literature and represents a significant research gap.

2.3.6 Heat Pumps

Heat pumps have long been identified as a future clean energy source for meeting building heat demand providing they can utilise renewable electricity. They can be categorised as ground source or air source heat pumps and have the advantage that they can also provide cooling in warmer seasons. They have high energy efficiencies with a typical coefficient of performances (COP) of around 3 to 4, meaning for one unit of electrical energy input you get 3 to 4 units of useful heating energy. Studies that consider heat pumps using the typical energy hub modelling procedure would model this COP as constant when in fact it is dependent on a number of factors including the part load percentage, outdoor air temperature, and ground temperature. Therefore, more realistic models must be developed to allow true optimal control of heat pumps within a multi-vector district energy system.

Several modelling approaches can be found in the literature. A thermodynamically derived, a dimensionless number relating borehole wall temperature to heat gain per unit length can be calculated. Commercial, numerical, heat transfer software can be used to model heat pumps with great accuracy. Artificial Neural Networks, ANN, have also been utilised as well as state space models [264]. Of these approaches, only ANN and state space models are simple enough to be utilised for real-time operational control, and thus only studies using these methods will be discussed in this section.

An Adaptive Neuro-Fuzzy Inference System, ANFIS, approach was used to calculate the COP of a ground source heat pump in [265]. Compressor inlet and outlet temperature, as well as the ground temperature were used as inputs to the model. A number of different membership functions were trialled and the best of which achieved an accuracy with a maximum error of 0.25%. Gang and Wang [266] used an ANN to predict the output water temperature of a ground heat exchanger which allowed better control of a hybrid ground source heat pump with a cooling tower. An ANN was used in [267] to predict heating capacity and compressor work done (and hence calculated COP) of a direct expansion geothermal heat pump. Inputs to the model were the temperature and pressure of the evaporator at the inlet and outlet, condenser inlet cooling water temperature, and the discharge pressure. A formal method of varying heat pump parameter set points was utilised to allow generation of a complete training data set in a relatively short period.

Zhang et al. [268] used a Radial Basis Function Neural Network, RBFNN, to model the performance of a ground source heat pump. The model was then used in conjunction with a particle swarm optimisation, PSO, to minimise operational energy consumption of the heat pump given a known building demand. ANN and ANFIS models were compared in [269] for calculating the COP of a ground source heat pump. The inputs to the two types of model were the same; namely, the evaporator inlet and outlet temperature, condenser inlet and outlet temperature, and the load side inlet and outlet temperature. Good accuracy between experimental results and model predicted COP were reported with slightly better results from the ANFIS model. However, these models only allowed retrospective COP calculation as the temperature inputs needed to be measured first meaning this cannot be used for model predictive control applications.

Both a nonlinear autoregressive exogenous, NARX, model and a reduced order state space model were used in [270] for prediction of mean ground loop fluid temperature. These were then utilised in a dynamic programming optimisation and nonlinear MPC optimisation respectively. Both models achieved excellent prediction and allowed calculation of heat pump COP to minimise the cost of energy consumption for a hybrid ground source heat pump system. Ahmad et al. [88] [89] used a quadratic equation to model COP of a heat pump. The developed model was then used to develop nonlinear model predictive control for a solar thermal system combined with a heat pump. In [271], heat transfer and power of a heat pump was modelled using quadratic regression curves based on simulated data. Similarly, models of the pump, fan coil units, piping network, heat storage and building space temperature were created. Whilst several heat pump variables were accurately predicted the authors did not envisage the potential to use this model for a building set point temperature optimisation aiming to minimise the energy consumption from the heat pump.

In summary, simplified models for calculating heat pump parameters do exist within the literature. These are most commonly based on neural networks, state space models or regression curves. However, many of the examples discussed use very specific parameters as inputs that would not necessarily

Table 2.5: Heat pump literature summary

Ref	Method	Input Parameters	Output Parameters	Model Accuracy
[265]	ANFIS	Compressor Inlet and Outlet Temp, Ground Temp	COP	CV = 0.136, Relative Error < 0.25%
[266]	ANN	Heat Exchanger Inlet Temp, Pipe Surface Temp, Backfill Wall Temp	Heat Exchanger Outlet Temp	RMSE = 0.034 - 0.062
[267]	ANN	Inlet and Outlet Evaporator Temp and Pressure, Inlet Cooling Water Temp, Discharge Pressure	Heat Energy Output, Compressor Power Consumption	CV = 2.45 and 3.41%
[268]	RBFNN	Building Load, Water Loop Mass Flow Rate, Ground Loop Inlet Temp	COP and Water Supply Temp	MRE = 4.53%
[269]	ANFIS and ANN	Evaporator Inlet and Outlet Temp, Condenser Inlet and Outlet Temp, Load Side Inlet and Outlet Temp	COP	RMSE = 0.06475 (ANN), RMSE = 0.05524 (ANFIS)
[270]	NARX and State Space Model	Model Regressors	Mean Circulating Fluid Temp	Fit-NRMSE = 98.63%
[271]	Quadratic Regression Curve Fitting	Compressor Speed, Circulation Pump Speed, Ground Loop Temp, Building Circuit Temp	Heating, Cooling and Power	Relative Error = 13.8%, 5%, 2.4%

Note - ANFIS (Adaptive Neuro-Fuzzy Inference System), COP (Coefficient of Performance), CV (Coefficient of Variation), RMSE (Root Mean Squared Error), RBFNN (Radial Basis Function Neural Networks), MRE (Mean Relative Error), NARX (Nonlinear Autoregressive Network with Exogenous Inputs), NRMSE (Normalised Root Mean Squared Error) be metered or easily forecasted for the next 24 hours. In an ideal case, for a holistic district energy model, the COP would be calculated based on the predicted energy demand, forecasted weather conditions and heat network temperatures.

2.3.7 Summary

Section 2.3 has reviewed the broad topic of energy modelling for district energy systems. Due to the interdependencies and connectivity between previously distinct energy vectors, a more holistic energy management strategy and modelling approach must be provided. Several approaches can be found within the literature; however, conversion technologies are often modelled simplistically. They often assume constant conversion efficiencies and no warm up or cool down periods which could lead to overall infeasible or sub-optimal solutions. Therefore, this section has reviewed modelling approaches for common energy generation and conversion technologies including CHP, boilers, solar PV, solar thermal, wind power, power-to-gas, and heat pumps.

The scope of this section was to determine suitable modelling for use in real-time optimisation and therefore with short computational periods. For CHPs and boilers, this can be achieved using relatively simple polynomial regression curves relating the part load factor to the efficiency, or through using multiple linear regression equations. This either requires manufacturer data or a small amount of experimental data. Solar energy prediction (both PV and thermal) is highly dependent on the prediction of solar irradiance. Currently, leading methods in the literature use machine learning models to forecast this variable. Then either a further machine learning model or solar equivalent circuits can be used to calculate PV output. In the case of solar thermal, machine learning models are recommended. However, as is often the case with machine learning models, a significant amount of historical data is required.

Short-term, wind power forecasting remains a significant challenge within the literature. This is due to the inherent stochasticity in wind speed and the lack of a consistent daily profile in comparison to solar power. The modelling of P2G systems is relatively unexplored within the current body of literature due to their status as an emerging technology still in an R&D phase. Therefore, no recommendation can be made on the suitability of different modelling approaches. It is expected that when operational data becomes available, linear or polynomial regression curves relating expected gas output to electricity input will be appropriate. Heat pumps are generally modelled by a COP or seasonal performance ratio; however, this is far from constant in reality. Many factors including part load, outdoor air temperature, and ground temperature can influence the conversion efficiency of a heat pump. From the reviewed literature, machine learning methods such as ANFIS or ANN could prove useful in modelling this behaviour.

2.4 District-Level Energy Management

The growth and requirement for increased energy decentralisation has been well established in the opening sections of this thesis. However, with the introduction of multiple energy generation sources, energy storage, flexible demand and variable energy prices, a significant control and optimisation problem has been formed. Simply put, which generation source should be scheduled for use at which time of the day? How can the energy storage capacity be utilised to provide maximum gain to the owner? Can buildings in a district work cooperatively to minimise their collective energy bill through a combination of load management and micro-generation? The literature reviewed in this section all propose methods to answer one or more of these key questions.

2.4.1 Microgrid Control

Model Predictive Control (MPC) is commonly applied to microgrid control problems as well as building optimisation strategies. An example of MPC utilised in this field is [272] which used a Mixed-Integer Linear Programming (MILP) optimisation procedure. The study aims to schedule renewable supply, battery storage, and a CHP. Case study results showed that operating as MPC rather than day-ahead control made better use of the energy storage device providing the consumer significant savings. Silvente et al. [273] also developed a rolling horizon MPC optimisation using MILP. The study aimed to maximise consumer profit whilst controlling PV and wind turbine generation, control of battery storage, and interaction with the power grid. Furthermore, the authors demonstrated that if the optimisation had control over some electrical appliances and able to delay their start times, the profit could be increased by 20%. However, the discomfort faced by consumers for the appliance delays is modelled arbitrarily and generation and demand is not predicted but known perfectly beforehand. Ma et al. [274] produced an MPC-based microgrid central controller to manage distributed generation and energy storage. Whilst the controller effectively shifts some load away from peak pricing periods, the control horizon is only one hour and the demand profile is perfectly predicted. A MILP-MPC strategy for managing the heat and electrical supply to a group of residential buildings in a microgrid setting was developed in [275]. Shared energy generation and storage are best utilised to flatten peak loads and hence reduce the cost of energy for the district as a whole.

MPC is used for a different purpose in [276]. Whilst many studies aim to schedule devises for the minimisation of cost, this controllers' objective is to maintain power quality within the microgrid despite the variable renewable supply. Electric vehicles were specifically considered within a microgrid setting in [277]. This study developed an aggregation and optimisation model for the inclusion of vehicle to grid battery storage in a local microgrid. Whilst one electric vehicle could only provide a small storage capacity, if aggregated the flexibility could become substantial. However, it is questionable as to whether users would accept their vehicle batteries being used like this and some form of financial incentive would be necessary. Clastres et al. [278] aimed to optimise a solar PV and battery system using MILP in a de-regulated electricity market where small-scale prosumers could bid to provide ancillary services to the grid. With perfect forecasting the optimisation produced a profit of €1.22, however, when prediction uncertainties were introduced this profit fell significantly to €0.50. This demonstrates the importance of including and managing prediction uncertainty in an optimisation study of this type. A potential solution to managing prediction uncertainty was proposed in [279]. The MILP optimisation method proposed a two stage optimisation, one with a horizon of 24 hours and timestep of 1 hour, and a short-term optimisation with a horizon of an hour and timestep of 5 minutes. The strategy was successfully deployed to a hotel-based microgrid case study with solar PV, a diesel generator, grid connection and battery storage.

A Mixed-Integer Non-Linear Programming (MINLP) optimisation strategy was experimentally validated used a microgrid testbed in [280]. The authors theorised a local electricity market for an 'islanded' microgrid. The optimisation controlled local generation devices within the context of the day ahead electricity market to minimise the cost of energy. The operation of a CHP combined with battery storage to meet thermal and electrical demand was optimised in [281]. This study uses a Colonial Competitive Algorithm, which is a meta-heuristic algorithm similar to a GA or PSO. However, this operates as a day-ahead optimisation and cannot consider or react to prediction errors and therefore assumes a perfectly predicted energy demand. Barbato et al. [282] used linear programming to schedule household appliances but also considered the effect PV panels and battery storage could have in this optimisation. Both single house optimisation and a group of houses working cooperatively was considered. Significant cost savings were achieved by consumers if they were more flexible with their device usage and have PV and battery storage.

Furthermore, if the district worked cooperatively it achieved significant reductions in the peak load and peak to average ratio which considerably decreased stress on the energy supply network.

2.4.2 District Heating and Cooling Control

Alongside the growth in literature aiming to better control local microgrid systems, many researchers have also developed methodologies to manage thermal energy generation components and systems. The thermal equivalent of a microgrid is a localised district heating (and cooling) network, which connects an often centralised energy centre to the consumers via hot (or cool) water pipes. An analytical optimisation using a multi-objective GA was applied to control the heat generation units of a district heating system in [283]. The dual objectives of increasing the profit to the energy centre and reducing CO_2 emissions were achieved. However, the demand was assumed to be perfectly predicted and the heat generation units were modelled simplistically with constant conversion efficiencies.

The coordination of a series of centralised heat pumps supplying buildings in a district is addressed in [284]. The authors display a cooperative optimisation strategy that exploits the flexibility provided by sharing centralised resources. The larger building in the district is able to achieve cost savings of 15% however the smaller buildings receive a small rise in cost raising issues of fairness. Furthermore, the buildings' thermal dynamics are modelled using fairly simplistic state space models that does not take into account internal equipment gains or occupancy. Razmara et al. [285] developed a bi-level optimisation that aimed to control building thermal energy demand and then checks the given solutions to ensure they do not breach district-level constraints. If these constraints are breached a second, district-level, optimisation strategy is carried out which feeds back results to the building-level optimisation. A case study based on a university campus with a ground source heat pump demonstrates a 25% reduction in cost without breaching grid constraints. Three different methods of controlling a residential thermal system containing solar PV, thermal storage and a heat pump were detailed in [286]. The objective was to balance the thermal comfort of the occupants with a desire to reduce peak load. The authors argued that a quadratic objective function produced the best balance between the two competing objectives.

A MAS approach to managing a multi-vector energy system with a CHP, heat pump, local resources and flexible appliances is detailed in [287]. The authors formulate their optimisation to minimise the use of grid electricity and heat from a centralised CHP and therefore maximise self consumption. However, the dual scales (building and district) lead to local minima as agents at a building level are not aware of additional flexibility elsewhere. Guan et al. [288], also aimed to develop a comprehensive optimisation strategy that satisfied both thermal and electrical demand including energy storage, renewable generation and ToU tariffs. The optimisation strategy effectively shifts cooling load by pre-cooling and utilising electrical energy storage to avoid purchasing electricity from the grid at high cost periods. Whilst the study does factor in small uncertainties in the solar PV power generation profile, the thermal and electrical demand profiles are considered completely accurate. In addition, the problem was linearised to allow the use of a MILP optimisation procedure, meaning that the part-load characteristics of the CHP were not captured. Jin and Ghosh [289] also aimed to optimise a system containing a CHP. The study showed that an MPC based approach could achieve significant energy savings and the larger the battery capacity, the greater the potential savings. However, once again detail on the building in the case study is lacking.

The control of a centralised campus cooling system was optimised using MPC in [290]. Every component of the system was modelled and validated using simplified analytical models. The objective of the control procedure was to maximise the COP of the system and minimise the electricity cost whilst meeting the cooling demand. When applied to the real site over a short time period the plant COP was increased by 19.1%. Hu et al. [291] also addressed the optimisation of a centralised cooling plant. In this paper, a decentralised memetic algorithm was deployed with the aim of reducing cost to a cluster of buildings. The decentralised approach was shown to be more cost effective than 'greedy' strategies where one building determines the solution for the whole district. A decentralised optimisation strategy was also favoured in [292]. The strategy aimed to control a centralised chiller and thermal energy store at a high level but also manage the lower level HVAC components. The authors argued that the problem would be too complex and time consuming if solved in a centralised manner. Therefore the problem was split into several smaller sub-problems. This solution was applied to a relatively simplistic case study building with only three zones.

2.4.3 Distributed and Market-Based Coordination

Due to increasing grid decentralisation, some authors have developed business models for inter-district energy trading and bidding. This moves beyond time-of-use tariffs, which set relatively regular pricing conditions each day, to a

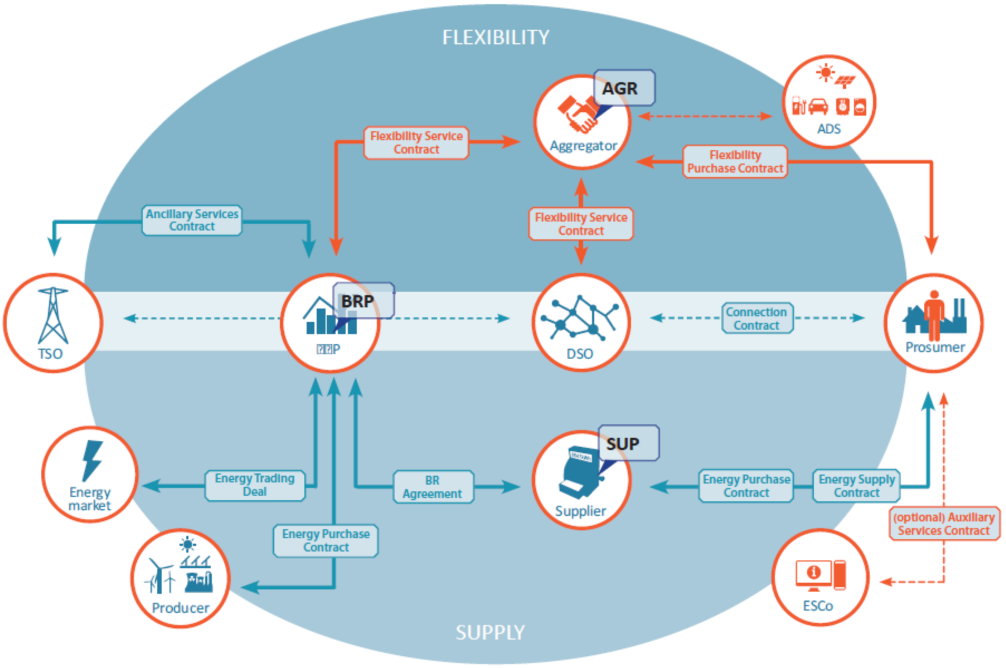


Figure 2.6: The USEF model of interactions between energy network stakeholders [293]

more real-time energy market. Many of the solutions outlined in the previous sections are based on centralised control and optimisation which may not be acceptable from a privacy or user comfort point of view in a multiple stakeholder district. The studies reviewed in this section deploy a decentralised optimisation strategy for which each individual consumer retains more control of their own energy management but operated within a wider market-based system. The most developed standard on an integrated energy market is given in the Universal Smart Energy Framework by the USEF Foundation, [293]. It clearly defines several stakeholders including the prosumer, the balance responsible party (BRP), the distribution system operator (DSO) and the transmission system operator (TSO). It outlines the interactions the stakeholders' have with each other and the key role an energy aggregator can play to provide flexibility in the system, Figure 2.6. The grid can request flexibility at specific times from a series of aggregators which in turn manage a portfolio of prosumers from which it can leverage and negotiate flexibility. Once agreement is reached and the decisions have been actuated, the grid must financially compensate the prosumer for their flexibility service according to pre-agreed conditions. Zhou et al. [294] developed a two-level control strategy for an aggregator or the BRP. Using day ahead forecasting for demand and generation, the optimisation strategy aims the minimise the cost of intra-day energy trading required due to unforeseen circumstances or poor predictions.

Fanti et al. [295], developed a district energy management system based on day-ahead pricing schemes and real-time power monitoring. In this model, buildings are required to submit day ahead energy consumption predictions. Then the actual consumption of the buildings is monitored and compared to the estimations to determine rewards or penalties. A demand response (DR) aggregator for a group of residential buildings is presented in [296]. The controller bids for energy based on real-time pricing fluctuations set by the DSO. This allows empowered consumers to shift their load, avoiding peak prices, to achieve cost savings. This is also greatly beneficial to the DSO as overall peak demands on the system will be reduced. In [297], a community controller acts as a virtual DSO to implement real time price variation to a group of smart homes. Domestic appliances operation times are shifted to reduce the peak energy demand. However, in this case study some residences receive increased costs even though the overall cost for the district is reduced. This raises crucial issues of potential unfairness that could arise.

2.4.3.1 Multi-Agent Systems Approaches

Agent-based controllers in the context of real-time price variation can also be found in the literature. Multi-Agent Systems (MAS) have the advantages of a completely scalable computing architecture, resilient to failures in communication, and potentially increased security as no agent will have access to every piece of information. The PowerMatcher software, a MAS market-based infrastructure, is detailed in [298]. PowerMatcher was utilised in [299]. In this study the author proposed that consuming and producing appliances are represented by intelligent agents. These agents submit the price that they are willing to pay or receive for their energy. Once all bids are assembled, the market clearing price is calculated. If this price is higher than the consumer agent is willing to pay, then it does not consume energy and waits for the next round. In a case study, the rate of over or underproduction from a wind farm is reduced by 50% and peak load is reduced. PowerMatcher was also used in [300]. It found that if the percentage of intelligent loads within a large district was increased, there is an almost linear decrease in peak power by up to 20%. PowerMatcher was enhanced in [301] to consider both electricity and heat in an integrated way which is important considering the increasing electrification of heat through devices like heat pumps.

Lagorse et al. [302], applied MAS to a hybrid renewable system. Each device had internal control logic and a ‘token’ is passed between devices to indicate which agent is in control of the overall DC voltage. The token is requested and passed between devices depending on their internal conditions.

Wide-scale MAS control of domestic appliances was simulated in [303]. An agent was based in the smart meter of each home representing the aggregation of several controllable and uncontrollable household appliances. A connected system of 5000 homes was theorised and in a simulated case study, energy peaks were decreased by up to 17%. The GRENAD, MAS framework was outlined in [304]. This framework aimed to provide a generic, modular and flexible platform to simulate and control smart power grids using MAS. A novel, semantic web ontology based on existing standards and the USEF framework was developed in [305]. The ontology aimed to provide a data infrastructure on which a MAS energy management platform could be deployed.

2.4.3.2 Game Theory Approaches

More traditional optimisation methods focussed at a district-level could lead to overall system optimal e.g. minimum total cost of district energy but could lead to cost rises for specific individuals within the district. These issues of unfairness could potentially be resolved by instead using a game theory approach to solving district energy management problems. Game theory approaches can more fairly model individual ‘players’ rational desire to minimise their own energy costs. Saad et al. [36] provides an excellent review of the game theory applications in a smart grid environment. The autonomous, distributed, and heterogeneous nature of the smart grid make game theory well suited to smart grid problems. The review argues that interactions and energy trading between micrgrids and the wider network can be modelled as well as interactions between the consumer and utility company regarding demand side management and load shifting.

A two-level demand side management game is developed in [306]. The lower level evolutionary game composes of a population of residential, household consumers choosing how much energy to purchase at specific hours from different utility companies based on their prices. The upper game is a non-cooperative game between the utility companies where they determine their generation amount and future energy price. Both games are proven to converge quickly, the method is shown to be scalable and results in a lower average price for the consumers and a lower peak to average ratio. Gkatzikis et al. [307] investigates the role an aggregator can play in a future smart grid setting. A three-level scenario involving 10000 households, several aggregators and a single utility is investigated. A day ahead, the utility advertises a demand shifting target and a price they are willing to pay for this. The aggregator then bids a certain level of demand shifting on behalf of their portfolio of households whom they compensate for their flexibility. The system is shown to be highly dependent on the reward the utility is likely to offer and the level of flexibility shown by the residential consumer. However, the study did show potential for a 15% reduction in operating costs where all three parties gain compared to a baseline, flat price scenario. A combined MILP and game theoretical approach is used in [308] to optimise the scheduling of controllable appliance to minimise the cost to a group of residential consumers working cooperatively. Wu et al. [309] uses game theory to optimally control household appliances of several residential consumers in an islanded microgrid with wind and gas generation. Using this method reduces the community energy bill by 38% even with imperfect, Markov chain, wind generation forecasts. If the forecasts are improved a further 21% saving could be achieved.

Rather than considering appliance scheduling, [310] and [311] use a game theoretical approach to optimise a smart grid in which a small percentage of users have dispatchable electricity generation and / or storage capacity. It assumes day ahead knowledge of user demands from which a pricing tariff is set. The active users then use their flexibility to minimise their own electricity bills which results in a flatter demand profile and hence lower prices. The users with greater flexibility (generation and storage) achieve very high savings around 80% but even the passive users see a reduction in cost around 15% simply due to the reduction in peak prices. Mohsenian-Rad et al. [312] suggests that dynamic pricing set by the utility encourages each individual user reduce their energy cost by reducing their peak to average ratio. However, the author argues that this is not necessary providing a district works cooperatively to ensure their collective peak to average ratio is small. To achieve this the authors' develop a distributed, game theoretical approach to minimise a collective district energy bill by scheduling their appliances iteratively and broadcasting their forecast energy consumption to their neighbours. This results in a 17% reduction in peak to average ratio and 18% reduction in cost.

2.4.4 Summary

This section demonstrates that when at a district level, the majority of optimisation studies aim to optimise the supply side of the energy infrastructure. This largely involves scheduling controllable energy generation devices and energy storage capacity around stochastic renewable energy supply fluctuating energy tariffs. In general, the demand-side is modelled simplistically, often assuming a fixed demand profile viewed as a constraint to be met within the optimisation. The demand profile is often considered to be perfectly forecast with no errors, which is unrealistic when deployed in real case studies. This means that many of the reported energy or cost savings would be reduced and user comfort constraints may be impinged. It is likely that an intermediate error management step would be required to adjust the schedule provided by the optimisation to fit with updated, observed constraints.

Despite the influence of non-linear part-load characteristics as discussed in Section 2.3.1, energy generation models are often simplified to ensure an entirely linear problem to allow the use of linear programming techniques such as MILP. Effort should be made to include part-load characteristics as well as minimum operational loads, ramp up rates and cool down periods to ensure feasible optimised solutions. There is a conflict between centralised and decentralised optimisation strategies within the literature. Decentralised solutions claim to be rapidly scalable, more secure, and more considerate of individual users preferences. Centralised optimisation strategies are more likely to find a global optimal. The literature has demonstrated that this can lead to potential issues of unfairness with some buildings scheduled to consume at higher pricing periods for the greater good of district as a whole.

2.5 Discussion and Research Gap

Evidenced by a thorough review of the existing body of literature, a significant research gap remains towards producing a truly holistic, integrated, building and district energy management platform. State of the art building energy management is required to be more active, context aware, and predictive in nature. Factors such as external weather conditions, occupancy, energy prices and local renewable supply must be integrated into control logic of building energy management systems which should target control at a zone-level rather than a building-level.

With an energy infrastructure becoming more decentralised and uncontrollable, the flexibility contained within building demand must be utilised fully to reduce cost to consumers and utilities simultaneously. Building demand should no longer be considered a constraint that must be met by supply-side optimisation, but as an active, controllable component of a modern, decentralised, multi-vector energy system. Studies that do consider the flexibility provided by buildings, model this in a very simplified way that may not fully capture the thermal dynamics within a building and therefore the impact on occupant comfort. Much of the recent research fails to consider that demand-side control can have a direct impact on cost of energy generation from the supply side. For example, if energy generation is localised at a microgrid level, peak load shifting could have a direct consequence on energy supply cost, as expensive backup generation units may not be turned on.

Therefore, a principle gap in the literature is the simultaneous control of both energy supply and energy demand. This demands a multi-scale approach, as demand will be largely controlled at a building-level, whilst energy supply is largely controlled at a district-level. To achieve a holistic, multi-scale, energy management solution, requires the merger of a supply-aware demand-side optimisation and a demand-aware supply-side optimisation. This could allow greater benefits through exploiting the combined flexibility on both sides of the problem.

To manage and control a modern, complex district, information and characteristics from various heterogeneous, multi domain, data sources must be linked via a robust communication infrastructure [313]. One such method to achieve this is based on developing a semantic representation of a district energy system which allows machine interpretable descriptions of the district to be defined. This can allow domains which have been considered in isolation to each other to be connected and integrated [314]. Leveraging semantic modelling could provide a district management platform a method to enable the exchange of data between different data models and software which may not use the same communication protocols to allow truly holistic energy management approaches. A semantic model of a district energy system can provide the foundations on which wider data analytics of optimisation techniques can be applied. Furthermore, utilising semantic web technology and ontologies allows a scalable and flexible approach to district modelling as additional concepts can be simply added and distinct domain ontologies can be mapped together.

Future research in semantic-based modelling could provide the link between the currently available Building Information Modelling, BIM, models and real time, operational data collected by sensors embedded within the building [167]. A unifying ontology that has knowledge of the buildings physical components and characteristics as well as access to BEMS sensory information would allow truly powerful and useful data analytics for a facility manager. This can provide the platform to allow prediction of future energy consumption, behaviour patterns and occupancy. Smart control algorithms could also be built on top of the ontology allowing resulting schedules and instructions to be sent for the BEMS to action. The base provided by the semantic modelling of a district could lead to a 3D visualisation of the district for facility managers, local authorities, or urban planners. The link with the sensory information of the district could allow relevant data, depending on the user, to be displayed in a more dynamic, clear and useful manner compared to current BEMS interfaces.

Given the rise in implementation of smart metering devices, time of use or real time energy pricing tariffs are likely to become more available and popular with consumers. These tariffs will allow engaged and empowered users to gain substantial cost savings over fixed rate energy tariffs by intelligently shifting their consumption to advantageous times. However, we cannot expect the average consumer to constantly monitor or understand energy price fluctuations and manually reset many of their devices to consume or stop consuming energy. This leads to opportunities for so called Energy Service Companies, ESCo's [315]. Consumers could effectively outsource their energy management and relevant data to 3rd party companies which would aim to provide energy cost reductions for the consumer and in return take a proportion of that saving. ESCo's would have to gain access to large amounts of user data and could provide virtual, cloud-based energy management. The recent introduction of commercially available, on demand, high performance computing, HPC, from cloud services companies such as IBM, Google, Amazon and Penguin could revolutionise what is achievable in building energy management. It could allow greater levels of data analytics, improved prediction models or even the use of more computationally intensive modelling techniques. Depending on the specific stakeholders involved in each district and their privacy and security requirements, several different business models for ESCo's could be explored:

- Internal Energy Markets - An internal energy market between the ESCo's clients could be formed. Users with complimentary load profiles or excess renewable generation could combine to form virtual energy sharing partnerships facilitated by the central grid and the ESCo. These consumers could be in different geographic locations and provide mutual savings for all parties and achieve greater prices for excess energy rather than selling back to the grid.

- Centralised Control - This control architecture would be more applicable for, natural, self-contained, districts with a single owner and a single utility bill such as University campuses, industrial estates or public sector buildings. In this situation, advanced MPC could be applied utilising the existing SCADA based system for data collection and actuation. The intelligence and decision making would be held in a control layer above the SCADA system.

- Intelligence Update - A more passive approach that ensures the user feels in control of their systems. The ESCo could carry out semi automated data analytics resulting in the feedback of simple suggestions to the user based on the data available. These could be slight adjustments to the current rules, for example to turn off the HVAC system an hour earlier. The user would then decide whether to implement this.

- Demand Response Coordinator - This architecture is much closer to the USEF framework. Initially each BMS would locally optimise their own day ahead demand. This would be fed to a district level controller to build a district demand profile. Using this knowledge and predictions of generation capacity, it could make decisions on how to flatten the overall demand profile. An iterative, negotiation based arrangement would take place to lead to a more optimal district demand profile for which consumers would be rewarded financially.

2.6 Conclusion

This Chapter has aimed to answer the first research question outlined in Chapter 1 which is re-stated here as:

How can the components found within a district energy system be modelled for the purposes of operational optimisation?

The literature reviewed throughout this Chapter clearly demonstrates that modern machine learning methods have been widely used throughout the state-of-the-art research. They have the capability to model not only building energy consumption but also energy conversion technologies including solar PV, solar thermal, wind turbines and heat pumps. The key criteria in assessing the applicability of modelling methods for operational optimisation was the ability to make predictions within a short computational period. Once trained, machine learning models can make predictions in near real-time. In addition to machine learning methods, simpler regression relationships could be used for energy conversion technologies such as boilers, CHP and heat pumps. If solar radiation is well predicted then solar equivalent circuits could provide an appropriate method for modelling solar PV generation. The state-of-the-art literature review and conclusions drawn from it was originally published in Reynolds et al. [316] and was reformatted for inclusion in this thesis.

In addition to answering research question one, the thorough literature review carried out in this Chapter has directly led to the remaining research questions and hence the contributions resulting from answering these questions. Chapter 3 will provide the approach to undertaking this research and explain the methods by which it was conducted and validated.

3 | Research Methodology

This Chapter will introduce the general methodology through which this research was carried out. It will outline the various stages that led to the research provided in this thesis as well as principles and approaches used. Following this, a more detailed explanation for each research question will be provided including the specific approach that was used to answer each question and provide validation for the proposed contribution. Finally, the core theory behind the main techniques used throughout this thesis will be provided. These techniques are Artificial Neural Networks, Genetic Algorithms and Model Predictive Control.

3.1 Research Methodologies

In order to explain the research methodology applied in this thesis, the core epistemological approaches will first be broadly summarised from Saunders et al. [317]. To illustrate the available research paradigms the 'Research Onion' model is presented in Figure 3.1 which should be read from the outer layers which inform the inner layers.

Positivism is a philosophical theory based on empiricism. It aims to produce generalisations based on observable phenomena. Similar to that of the scientific method, it proposes clear research hypotheses which can be tested, verified or refuted through credible, quantifiable and factual data. The goal is to describe relationships that facilitate the verifiable predictions of different scenarios. Realism is a similar philosophical stance largely based on the scientific method. However, rather than aiming to model and predict phenomena, realism aims to explain and comprehend the actual reality which is independent of the way the mind perceives it to be. The positivist and realist approaches are in contrast to the interpretivist philosophical stance. This paradigm does not believe in a universal, objective truth and instead focusses on the way in which social actors perceive the world. Hence, this approach lends itself to a more qualitative, subjective research. The final research philosophy is pragmatism. This philosophy rejects the rigid nature of the previous research philosophies.

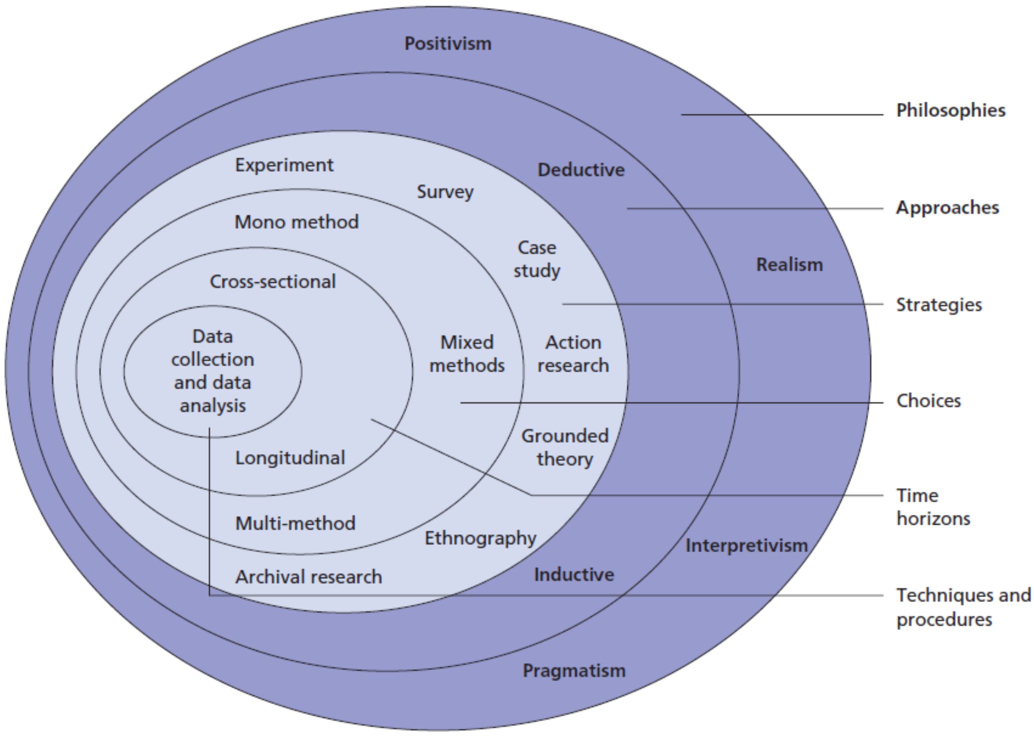


Figure 3.1: The ‘Research Onion’ [317]

Actual research projects rarely fall neatly within a single methodology, therefore pragmatism argues that one should combine any research methods required which best suit the specific problem, hypothesis or research question.

Whilst the research carried out in this thesis contains large elements of positivism, through development of case studies and the testing of hypotheses, the pragmatist research philosophy has been followed throughout this research project. Taking the pragmatic approach enables flexibility throughout the construction of the thesis. Largely quantitative methods have been used verify the performance of energy management strategies developed during this research. However, a significant proportion of the research period was spent carrying out action research, integrated within ongoing, collaborative research projects. The lessons learned from interactions with stakeholders and experts helped to mould and define the research methods deployed in this thesis.

3.2 Research Approach

The research methodology was broken down into three distinct phases. Firstly, background research into the existing field of research and current applications was explored through a literature review. Secondly, the research goals and questions were refined and confirmed through participation and contribution to larger research projects. Finally, the iterative learning and research procedure carried out throughout stage two built the foundations for the most significant contribution detailed in Chapter 6.

3.2.1 Stage 1

Initially, a more theoretical analysis of the existing research gaps was conducted through a thorough literature review as provided in Chapter 2. This process aimed to synthesize the existing body of work, highlight the strengths and weaknesses, and crucially pinpoint the research gaps. This stage of the research methodology largely framed the development of the central hypothesis and research questions. It then follows that answering the hypothesis and research questions formed the main basis for the remainder of work described in this thesis. The literature review identified the existing energy management challenges faced at both a building and district-level. Specifically, the requirement for a zone-level, predictive building heating controller and an intelligent district energy generation optimiser that factors in stochastic renewable energy generation and energy storage. Crucially, these independent processes should be integrated to allow simultaneous control of supply and demand which is a topic that is largely neglected within the existing literature.

3.2.2 Stage 2

Once the research gaps were identified, the research approach moved into a second phase of participatory support to larger, Horizon 2020, research projects namely PERFORMER[1], THERMOSS[2] and PENTAGON[3]. Naturally, the support provided to these projects started as relatively minor and eventually built to more significant contributions towards the latter stages of this research. Active integration with a diverse range of stakeholders and challenging case studies was viewed as a pivotal learning experience which directly fed into the work of this thesis. Furthermore, by engaging with, and pitching solutions to, pilot site facility managers, crucial feedback was provided to ensure all future work accurately addressed the real life constraints faced in these scenarios.

The PERFORMER project focussed specifically on building energy consumption and the performance gap that is often found between predicted energy consumption of buildings and the actual energy consumption recorded during the operational phase. The project deployed hardware within pilot sites

[1] http://performerproject.eu/
[2] https://thermoss.eu/
[3] http://www.pentagon-project.eu/

to extract and assimilate BMS sensor data into a cloud-based data warehouse. Intelligent data analytics were then applied to the stored data to automatically detect faults, anomalies and provide new intelligent rules to reduce energy consumption. Within the context of this research, the PERFORMER project provided valuable insight and experience on detailed energy performance modelling of buildings, machine learning based prediction models, and the real demand for a more intelligent, interventionist and predictive building energy management system than the existing static, rule-based BMS currently used. Therefore, the knowledge gained from participation in this project reinforced the importance of research question 2 and informed the development of the dynamic, predictive, zone-level controller described and implemented in Chapter 4.

Both THERMOSS and PENTAGON aim to intelligently manage energy at a district scale. THERMOSS specifically targets the next generation of low temperature district heating and cooling systems and the retrofitting requirements to adapt existing buildings for connection to these networks. The PENTAGON project aims to develop a holistic, integrated platform to manage a multi-vector energy system and to explore the potential of power-to-gas technology at a district level. These two projects have aided the development of scenarios in which district energy optimisation is required. Furthermore, through the interaction with facility managers and pilot sites, the operational constraints they face have been communicated and implemented in this research. For example, a CHP is typically inflexible within a district energy centre. Practitioners were eager to emphasise their relatively small operational range and the maintenance required if cycled too frequently. Working within these research projects emphasised the demand for a robust district energy management system that appreciated generation unit constraints and modelled part load characteristics. In addition, they illustrated the requirement for predictive control systems to utilise energy storage to minimise generation cost as developed and implemented in Chapter 5.

3.2.3 Stage 3

The final stage of the research approach was to take the knowledge gained through the iterative, participatory learning in Stage 2 and apply it to a larger problem culminating in the most significant contribution of this thesis. The literature review and research projects have demonstrated that building and district energy management are largely considered as separate entities. Given the close interdependence between the two fields it seems natural to attempt to close this gap. Whilst researchers in the past have aimed to control both energy supply and demand simultaneously, they often lack the detailed modelling in one or both of the aspects. Therefore, the approach provided in Chapter 6 aims to directly control both building energy demand as well as district energy generation and energy storage to achieve a holistic, district-wide solution. Effectively, this is achieved by taking on board the learnings found during stage 2 and combining the contributions of both Chapter 4 and Chapter 5.

3.3 Case Study Design and Validation

The previous section outlined the general approach used across the PhD study to build towards a significant contribution to the body of knowledge. This section will detail the process by which each research question was answered and how the outcomes were validated. In the case of research questions 2, 3 and 4, different optimisation and control methodologies have been developed and applied to the relevant field. To demonstrate the methodologies' effectiveness, and hence provide evidence for the answers to each research question, the individual methodologies were applied to specific case studies. These case studies are all simulation-based to allow full control of factors such as weather and occupancy, reproducibility of results across different scenarios, and to provide direct comparison between the optimised scenario and baseline strategy. Every effort has been made to make these case studies as realistic as possible by feeding in learnings from the projects and through interactions with specialists and practitioners.

3.3.1 Building-Level Control

Chapter 4 aims to address research question 2; *Can predictive control of building energy demand with consideration of external factors lead to reductions in energy cost and improve demand-side flexibility?* The case study was based around a simulation model of the authors' office building in Cardiff. This was chosen as the building was relatively small with only 6 conditioned zones allowing detailed modelling. It is a multi-purpose building with different types of zones including office spaces, a meeting room, reception and kitchen providing a more interesting and complex example with a requirement for zone-level control as opposed to a more homogeneous building. Furthermore, access to the building was unproblematic, allowing easy measurement of building geometry and equipment as well as surveying of occupants to build realistic schedules. To validate the performance of the proposed building control methodology, the results were compared to a standard, baseline scenario. This baseline scenario applies the same heating schedule to the entire building which is the case in reality. It follows a pre-determined heating set point schedule of 12°C when unoccupied, and 21°C when during occupied hours. As the simulation models in the optimised and baseline case are absolutely identical apart from the decision variable in the optimisation methodology, comparison can provide assessment of potential optimisation savings. Furthermore, the difference between setting a building-wide heating set point temperature and a zone-level set point temperature will be analysed.

3.3.2 District-Level Control

The case study outlined in Chapter 5 aims to address research question 3; *Can taking an optimisation-based approach to the control of district heat generation improve upon existing rule-based priority order strategies?* To develop this, an entirely simulated district energy system including the supply and demand is designed. The design of both the supply and demand was greatly influenced by the research projects outlined in Stage 2 of the research approach.

To model a realistic energy demand, reference building EnergyPlus models from the US Department of Energy were used. As demonstrated via the PENTAGON project, it is important for the buildings connected to a district heating network to have some level of constant, year-round base load. In the case of 'The Works' in Ebbw Vale (a PENTAGON pilot site), the base thermal load is largely provided by swimming pools in a sports centre. In the case study developed for this research, it is provided by a hospital and hotel. In total five different buildings were selected to provide the demand profile for the case study district. Following analysis of the district heating demand, standard design procedures could be used to size the energy generation units which is outlined in greater detail in Chapter 5.

The chosen energy supply configuration is inspired largely by the scenarios used in the PENTAGON project. The aim was to create a multi-vector energy centre combining gas, electricity and heat networks in a single case study. To achieve this aim, generation and conversion units from different case-studies were merged to provide a complex, modern district energy system. To validate the performance of the optimisation methodology outlined in Chapter 5, it was compared to a static rule-based operation which formed the baseline scenario. The baseline scenario is a typical priority order strategy depending on the current demand. This is the current strategy deployed at 'The Works' pilot site and is therefore a fair representation of reality to benchmark against.

3.3.3 Combined District and Building Control

The combined building and district energy management strategy provided in Chapter 6 uses the same district utilised in Chapter 5. It aims to use this case study to tackle research question 4; *Can integrated, holistic control of both energy supply and energy demand lead to greater economic and environmental benefits than independent control?* The same logic and assumptions behind the creation of the case study still hold true. The crucial difference between Chapter 5 and Chapter 6 is that the demand of one of the buildings within the district is now controllable through adjustment of the heating set point temperature in a similar manner that proposed in Chapter 4. Only direct control of the office building is available in this case study. The aim here was to limit the amount of decision variables for the optimisation, and yet provide a proof of concept for this kind of combined supply and demand control. In particular, the office building was selected as this type of building would be the most likely to acquiesce to the removal of direct control over their heating systems in comparison to a hospital, hotel or residential apartments where comfort is king. In terms of validation for this case study, the optimisation outcomes can be compared to the same baseline scenario as the district level control outlined above. In addition, comparisons can also be drawn to the optimised results from Chapter 5 to illustrate the potential improvements in terms of cost of energy that can be achieved by allowing direct control of supply and demand.

3.4 Techniques

This section aims to briefly introduce the background theory behind the core techniques utilised throughout the remainder of this thesis. As these techniques are used in several of the following Chapters they will be discussed here in a generalised way to avoid duplication of this theory elsewhere. Each technique discussed in this section is well established within the field and the motivation for using each method will be discussed. These subsections do not aim to convey a comprehensive detailing of each method but a generalised knowledge to allow the reader to understand their application to the specific case studies throughout this thesis. Where relevant, more detailed sources will be referenced should interested readers require more information.

3.4.1 Artificial Neural Networks

The ‘Perceptron’, the foundation of modern Artificial Neural Networks, (ANN), and machine learning, was developed and published in 1958 by Frank Rosenblatt [318]. This seminal work provided a mathematical model of a synapse within the human brain with the hope of developing a machine capable of learning. Whilst this was a significant breakthrough, initial application of the perceptron was limited due to it's fairly primitive structure and ability to output either 1 or 0. It took until the 1980's for the potential of perceptrons to re-emerge in the form of ANN which are effectively layers of interlinked perceptrons. Due to the relatively simplistic building blocks of these multi-layer networks, the internal weights of the network could be adjusted with respect to the prediction error through the method of backpropagation [319]. These discoveries led to increased development and interest in ANN and machine learning leading to alternative ANN configurations such as recurrent neural networks, deep neural networks, Boltzmann machines and radial basis networks. These have been successfully applied to a wide range of modern problems such as image recognition, natural language processing and time series prediction [320] in several fields such as engineering, medicine, economics and psychology [321].

Chapter 2 demonstrated that ANN have been used extensively to effectively model various components within an integrated energy system. As well as an established pedigree within the field, ANN are simple to generate, deploy and integrate with additional procedures due to existing libraries and toolboxes. Therefore, throughout this thesis feed-forward backpropagation neural network with two hidden layers have been used to model several parameters such as building energy consumption, indoor temperature and solar energy generation. In all cases, these models were trained and implemented via the MATLAB Neural Network Toolbox. Whilst a wide range of ANN are available in the literature, from this point onwards all use of the term ANN will specifically refer to a feed-forward backpropagation neural network and the remainder of this section provides a brief introduction to operation of these networks.

In order to understand the operation of an ANN, a schematic representation has been provided in Figure 3.2 including a magnified section detailing the mathematical procedure at each neuron within the network. As shown in this example, three normalised inputs, I, are provided. Each of these inputs is multiplied by a specific set of weights, w, which are associated with each connection. Each neuron also has a specific bias term, b, associated with it. At each neuron, the sum of the inputs multiplied by the weights plus the bias term is calculated. The neuron output is then passed through a transfer function, common methods include tansig (shown in Figure 3.2), logsig and linear. The resulting number after being passed through the transfer function then becomes an input to the following layer. This procedure is completed for each neuron until the output layer is reached and the overall network output(s) are

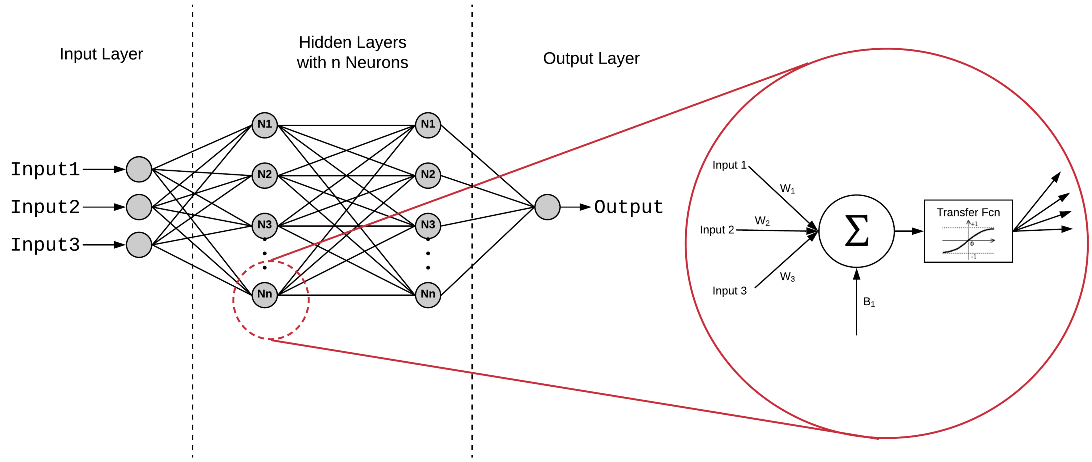


Figure 3.2: Diagram of a generic feedforward artificial neural network with two hidden layers

calculated.

Explaining the mathematical operation of a neural network doesn't necessarily explain how they can produce predictions so effectively. The intelligence of an artificial neural network hinges on the effectiveness of the training algorithm applied to it which sets the weights and bias of each connection and neuron. Several training algorithms exist so the description included here will aim to give a generic overview of the procedure. To effectively train an artificial neural network a substantial training data set is required. During the training period, both inputs and outputs are known to the algorithm. Based on these values, the algorithm iteratively adjusts the weights and biases in an optimisation procedure to minimise the sum of the error or mean squared error of the entire training dataset. Once the training procedure has been completed, the weights and biases are fixed; and once new inputs are given, an output prediction is produced.

Often a validation dataset is also required during the training procedure to prevent the phenomena of overfitting. Overfitting is essentially the network learning the specific training data that it is provided rather than learning the general trends and relationships between inputs and outputs. Thus when trialled, on an unseen dataset, the prediction performance becomes much poorer. During each iteration (or epoch), unseen validation inputs are provided to the network and the sum of error between targets and predictions is calculated. If the sum of the error on the validation dataset starts to grow relative to the error found when using the training dataset, this is a signal that the network has started to overfit to the training dataset. In this case the training procedure is forced to terminate early.

3.4.2 Genetic Algorithms

Initial research in trying to develop a computational model of the biological process of evolutions was conducted in the 1950's and 1960's. However it took until the 1970's for genetic algorithms (GA's) to be popularised through John Holland's *Adaptation in Natural and Artificial Systems* [322]. Inspired by Darwinian evolution, GA's are a branch of evolutionary algorithms which itself is a branch of metaheuristics. GA's have several advantages over traditional optimisation techniques such as calculus-based methods. Firstly, GA's simultaneously search many points across the whole solution space which is useful for problems with several local optima. GA's can also be applied to non-smooth objective functions where it is not possible to find the derivative. This is useful in cases where exact, deterministic, mathematical modelling of the objective with respect to the decision variables is not possible (such as the use of black-box models) and for non-continuous decision variables [323]. These advantages are also true for other metaheuristic algorithms such as particle swarm optimisation or ant colony optimisation. However, GA's have been chosen for use throughout this thesis as the optimisation methodology. This has been informed by the literature review in Chapter 2 which found GA's were well established in previous work as well as two recent review papers which stated that GA's are one of the most popular optimisation techniques applied within the field of building and energy optimisation [324, 325]. The remainder of this section will give a generic guide to the inner mechanisms and processes found within a GA which will be contextualised in later chapters with specific problems.

Genetic algorithms have a number of internal procedures which they iterate through in order to trend towards a more optimal solution. Namely, these are initialisation, fitness determination, selection, crossover and mutation. Many different adaptations of GA's can be found in the literature with their own procedures and functions but the optimisation process described in this section will relate to the GA method from the MATLAB global optimisation toolbox. A flowchart of the procedure is given in Figure 3.3.

During the initialisation procedure, a population of randomly generated feasible solutions is produced. Each solution within the population is called an 'individual' and the decision variables are encoded to each individual as a vector of 'chromosomes', with each chromosome representing one decision variable. If desired, the initial population does not need to be random. If the user can produce some sensible starting solutions through heuristics these can be provided to the GA and potentially speed up the optimisation convergence.

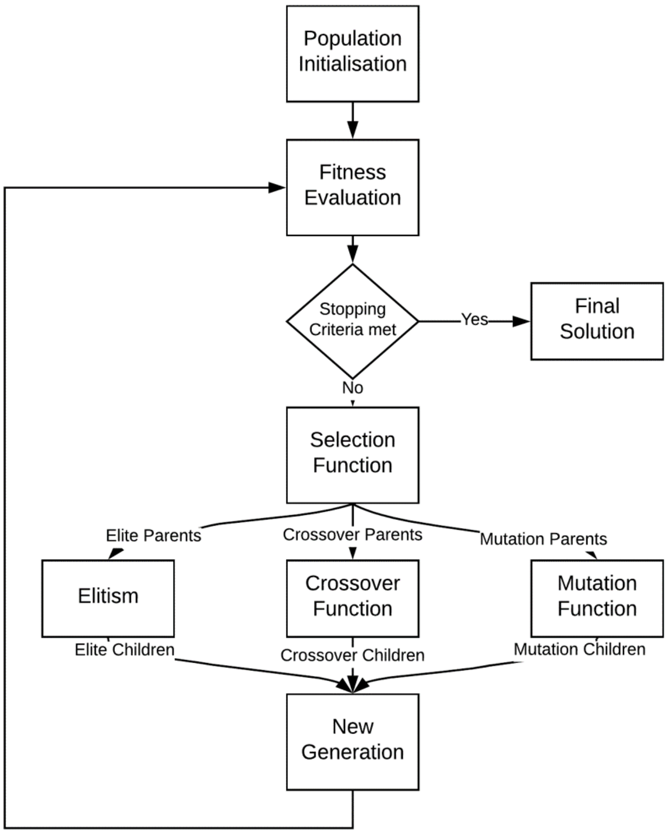


Figure 3.3: Flowchart showing the procedure of MATLAB's Genetic Algorithm

Once the population of solutions has been generated, each solution is evaluated for fitness against a pre-determined fitness function which relates the decision variables to the optimisation objective. The fitness function can range in complexity depending on the defined problem. It can be as simple as one equation or use these decision variables as inputs into a distinct simulation model. Assuming a relationship between input decision variables and output objective, a GA is capable of handling a variety of optimisation problems.

Following the fitness evaluation, individuals are ranked based on their fitness from best to worst. This ranking is used by the selection function to determine the likeliness that each solution will proceed as 'parents' to the crossover and mutation stage. Several methods exist to select select individuals from the previous population. The aim of these methods is to ensure that quality solutions proceed to the next generation yet diversity is maintained within the population hence the reason why the x best solutions are not automatically selected. One such method is 'Roulette' where each individual receives a section of a wheel proportional to their fitness rank. The wheel is 'spun' by generating a random number which corresponds to the selected individual. An alternative methodology is 'Tournament' selection whereby a set amount of individuals (usually 3-5) are chosen at random and the individual with the highest fitness

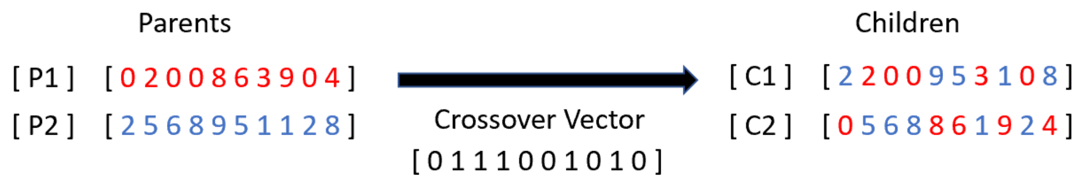


Figure 3.4: An example of the Scattered crossover function with parents on the left recombined according to a binary crossover vector to form child solutions on the right

is chosen to proceed as a parent. Both of the described selection functions find a balance between a bias towards the better solutions and the possibility to retain a diverse range of solutions.

Once the selection function has determined a set of parents they are split between crossover and mutation. The splitting fraction is determined by the user although it is common that a greater proportion of parents continue to crossover rather than mutation (around 80% is typical). During the crossover procedure, parents are paired and 'mate' to produce 'child' solutions. The broad aim of crossover is to recombine two existing solutions in a semi-random way to generate new solutions. Once again, several methods are available within the literature to achieve crossover. An example is the 'Scattered' method where a binary vector with length equal to the number of decision variables is generated. The position of the 1's indicate where the child's chromosome is inherited from the first parent and the 0's indicate a chromosome inherited from the second parent. A second child can be generated from the inverse of this, i.e. 1 indicated inheritance from the second parent and vice versa. An example is shown in Figure 3.4.

Parents that are not sent through the crossover procedure pass through a mutation function. The sole purpose of the mutation function is to ensure 'genetic diversity' within the population of solutions in order to avoid getting stuck in local optima. If crossover was used in isolation, there is a possibility that some of the solution space will never be searched if a value is missing in the random initialisation. Mutation works by randomly changing chromosomes within an individual. One method of mutation is the 'Uniform' function where a binary vector equal to the length of an individual is generated. Each value within this vector has a set chance of being a 1 (usually relatively low, around 5-10%). If the value is a 1 the corresponding chromosome in the parent is discarded and a new value is produced. This may be random or generated via an alternative method. An illustrating example is also provided in Figure 3.5.

In additional to crossover and mutation, some GA procedures will use the

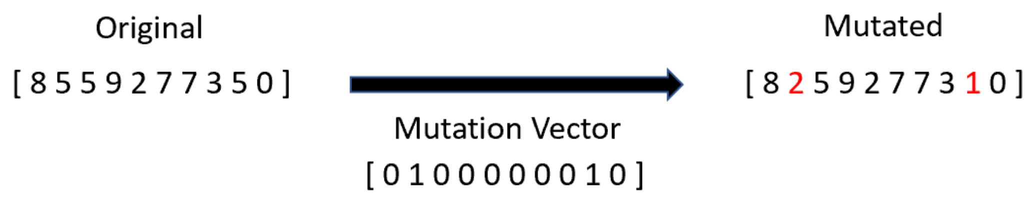


Figure 3.5: An example of the Uniform mutation function with the original parent on the left and the resulting mutated child on the right

concept of 'elitism'. If used, this takes a few of the best solutions in the population and directly copies them into the following generation to preserve these solutions. In the MATLAB GA procedure, the elite individuals are removed and then the remaining parents are split into crossover and mutation. However, the use of elitism and the order of operation between crossover and mutation can vary depending on the specific type of GA that is used.

Once the children produced by the elitism, crossover and mutation function have been collated, this forms the next generation of individuals. This iterative procedure of producing successive generations of solutions will continue until a pre-defined stopping criteria has been met. The stopping criteria can relate to a several different parameters. It can be based on a maximum allowable number of generations, maximum time limit or the rate of change in optimal solutions over generations.

3.4.3 Model Predictive Control

Model Predictive Control (MPC) is a form of direct digital control with capabilities to handle systems with multiple inputs and multiple constraints. Furthermore, it has the advantage of being able to assess an entire schedule of future actions rather than just a single action at the current time. This ensures that the controller does not just make 'greedy' decisions for maximum short-term gain but considers a longer-term, more predictive approach. MPC controllers normally sit a layer above more traditional control mechanisms such as proportional, integral and derivative (PID) controllers to overcome their lack of foresight and stability issues [326]. Recent reviews concluded that MPC is both a popular and effective approach in the literature to manage energy use within buildings [324, 327]. The advantages of MPC include it's ability to factor in variation in external factors such as occupancy, weather and pricing signals, it can exploit a building's thermal mass, and it can shift load from energy peaks.

Broadly the MPC procedure works as follows. The control problem will have both a prediction horizon T made up of N discrete control steps of size t. The control procedure will aim to optimise one or several input signals or schedules over the entire control horizon T. This is achieved through an internal model which can accurately predict the output signal as a function of the inputs signals (amongst other variables). This model is integrated with an optimisation procedure which can find the optimal or near-optimal input signal to minimise or maximise the selected objective. However, it will only implement the input signal over the first control step t before re-optimising and going through the entire MPC procedure again. This 'sliding window' approach ensures that the control procedure has the foresight to make intelligent long-term decisions whilst also remaining agile enough to react to changes in circumstances such as disturbances or forecast errors.

For greater clarity on the MPC procedure a generic diagram showing three consecutive timesteps is given in Figure 3.6. Note how the future input signal from t_0 to t_1 is implemented in the following timestep but the remainder of the future input signal is free to change to react to updated forecasts or errors in previous predictions. This also has a direct consequence on the future, predicted output signal. A final point to notice is the distance between t_0 and T is identical in the case of all three timesteps, it has simply been translated to the right by a time of t, as this time has been allowed to pass after the initial control procedure was started.

3.5 Conclusion

This Chapter has aimed to outline the core methodology used to conduct this research project. The Chapter began by providing a brief introduction to the available research methodologies and justification for the methodology chosen in this case. It detailed the research approach which was made up of three stages; a thorough literature review, iterative learning through participation in research projects, and finally application of the gained knowledge to extend the state-of-the-art. To tackle the research question provided in Chapter 1, a series of case studies were developed. This Chapter describes the case studies and illustrates how they were formed through interaction with real pilot sites. Finally, a brief introduction to three core techniques was provided. Namely, these are artificial neural networks, genetic algorithms, and model predictive control. These techniques re-occur throughout the thesis so are best explained at this stage.

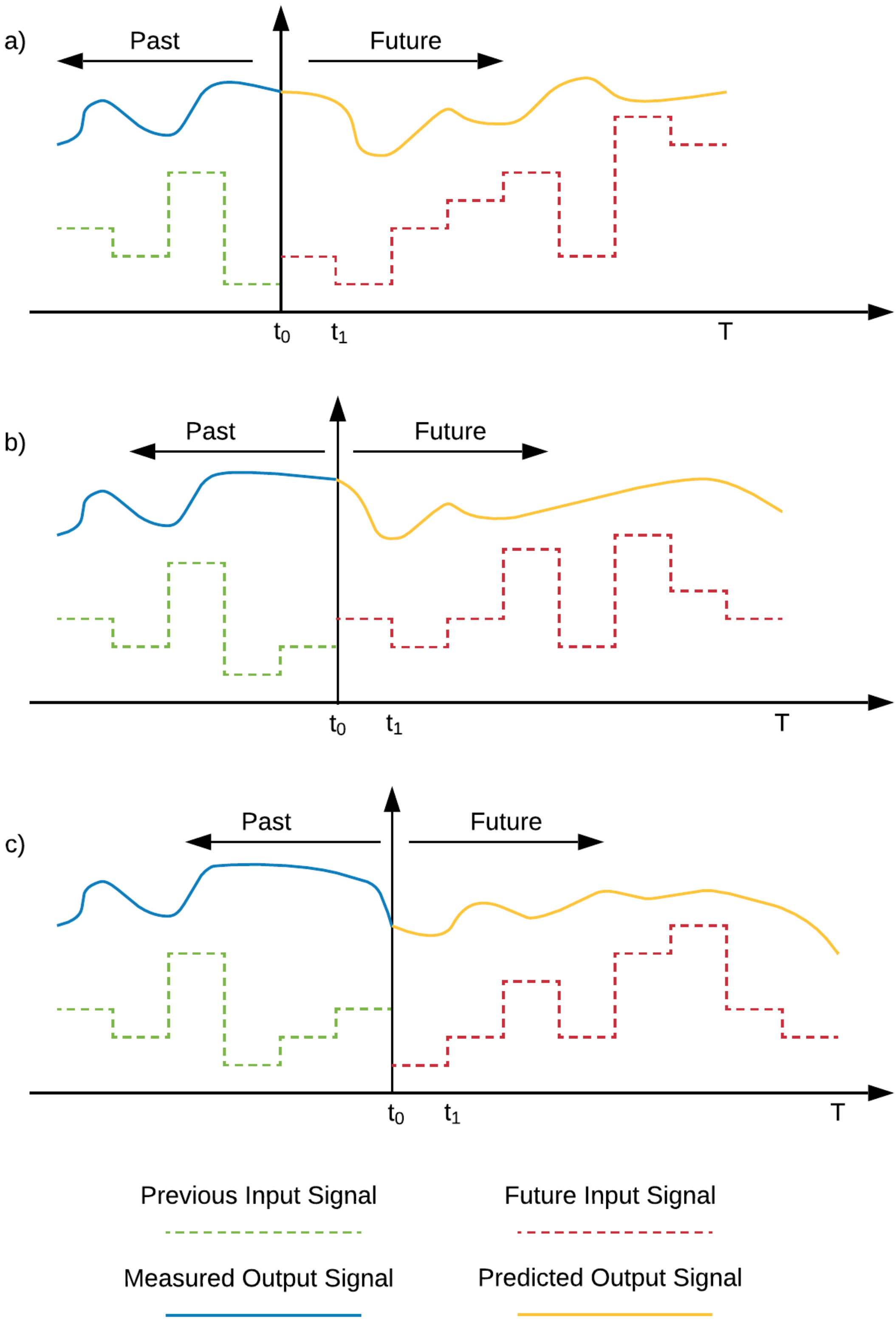


Figure 3.6: Model predictive control procedure - a) Timestep 1, b) Timestep 2, c) Timestep 3

4 | Building-Level Energy Management

As demonstrated in the literature review provided in Chapter 2, the optimisation of building energy demand is an active research field with several proposed methodologies. This chapter will outline the modelling and optimisation methodology behind a novel zone-level building heating controller. The performance of this solution will be compared to a static, baseline scenario to demonstrate the effectiveness of a more context aware, predictive controller.

4.1 Revisiting the Research Question

Specifically, this chapter aims to address research question 2, restated here as:

Can predictive control of building energy demand with consideration of external factors lead to reductions in energy cost and improve demand-side flexibility?

To provide validation of the proposed method, the optimisation will be applied to a case study building and will be compared to a baseline scenario which uses traditional thermal controls. Additional comparisons will also be made against a controller that uses a similar methodology but applied at a building-level rather than a zone-level. All controllers will be operated as day ahead controllers, meaning they optimise once at the beginning of the day, and as MPC where they optimise every hour. This range of operating modes will allow a wider evaluation of the importance of zone-level control vs building-level and MPC vs Non-MPC. To assess the flexibility of building demand control, the optimisation methodology will be able to minimise energy consumption or the cost of energy subject to a ToU energy tariff. The ability to shift energy demand subject to external energy costs will be increasingly important in the following chapters.

The optimisation methodology described in this Chapter was originally published in Reynolds et al. [328] and reformatted and expanded for this thesis.

This work built upon the initial, proof of concept investigations conducted in Reynolds et al. [114].

4.2 Modelling Methodology

The case study building that was modelled and simulated to demonstrate the optimisation process was the authors office building in Cardiff, UK. This is a relatively small office building with six main thermal zones; three separate office zones, a kitchen, a reception area and a meeting room. The building has an approximate footprint of 185m^2 and typically the builing is occupied by around 20 people during weekdays. The building was chosen as it was easy to access (given it was the authors place of work), had zones with different functions and had relatively few conditioned zones to maintain a tractable optimisation problem. The process of modelling this building took several steps; initially the building geometry was captured using a 3D laser scanner, from this the semantics were captured through a Revit BIM model, this was converted into an energy model in DesignBuilder, which was used to generate training data for a surrogate ANN model.

4.2.1 Capturing the As-Built Geometry

As the building is relatively old, digitised floor plans were not available. Hence, an as-built representation of the building needed to be captured. To achieve this a FARO Focus X Series 3D laser scanner was used. The scanner casts a laser on the surrounding objects and detects the level of energy deflected back to the scanner to build a series of points with x, y and z coordinates. The combination of these series of points forms what is known as a point cloud. Images taken by traditional cameras can then be overlaid on the point cloud to achieve a photo-realistic 3D representation of the scene. Typically, multiple scans will need to be taken from several angles or, in the case of a building, in several rooms. Two scans are ‘chained’ to each other semi-automatically through the definition of common points between successive scans. This is typically achieved using fixed reference points such as chequerboard posters. The point cloud representation of the case study building is shown in Figure 4.1 with surfaces coloured based on their orientation.

4.2.2 Conversion to BIM

The point cloud itself does not hold much useful information beyond the distances between surfaces and objects. To capture the real semantics associ-

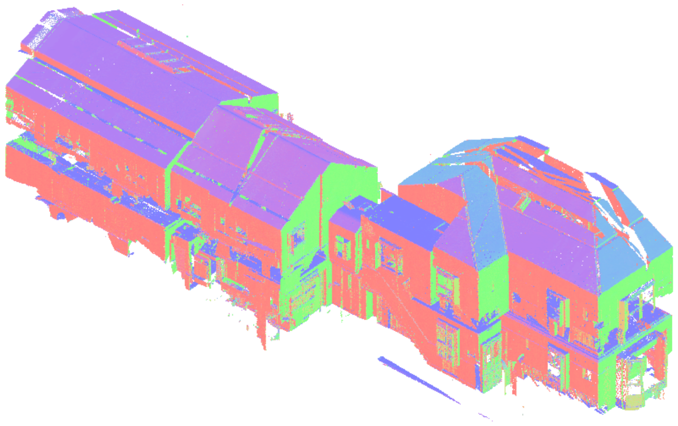


Figure 4.1: Point cloud representation of the case study building

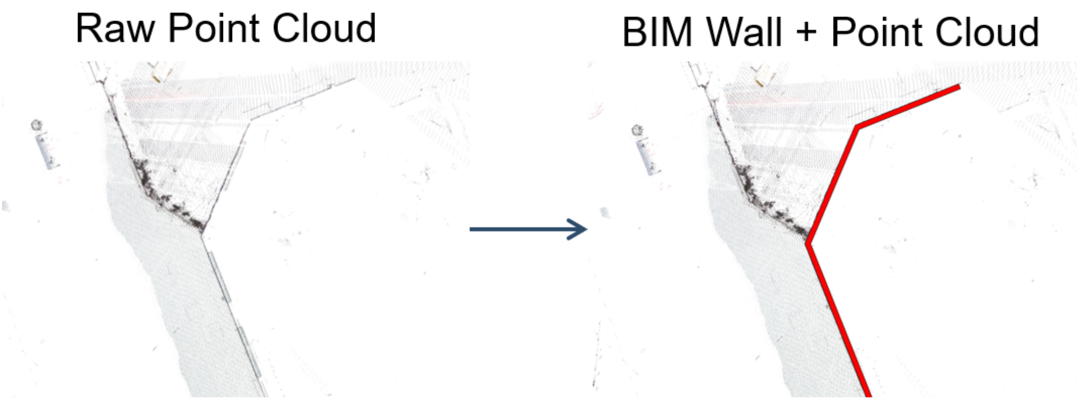


Figure 4.2: Process of generating a BIM model from a point cloud; left - original point cloud, right - point cloud with a BIM wall object

ated with the building a BIM model was produced using Autodesk Revit. Revit has the capacity to import point clouds to the workspace which is then essentially used as a guide to produce the BIM geometry. Illustrations of the modelling of walls are shown in Figure 4.2. By slicing the point cloud on horizontal planes, the position and shape of walls are clearly identifiable. Similar processes can be used to position the levels of the building, the roof structure, and the window sizing and positioning. This process concluded in the BIM model shown in Figure 4.3. Once represented as a BIM model, additional semantic information can be added to the model, including the thermal zones, construction materials, and material thickness.

4.2.3 Energy Modelling

Whilst BIM software, such as Revit, is beginning to integrate building energy analysis and simulation, third party software tools such as IES, TRNSYS and EnergyPlus are more detailed, customisable and trusted by both industry and

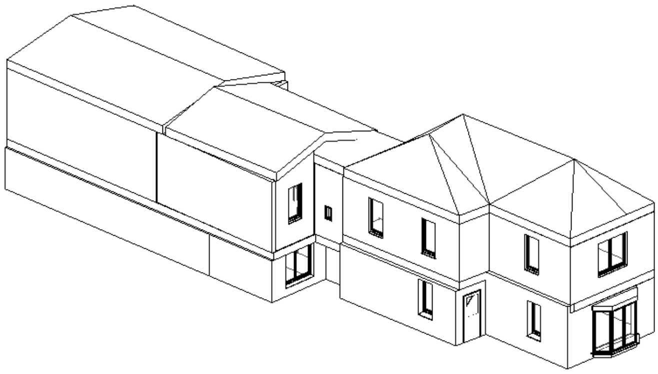


Figure 4.3: Revit model of the case study building

academia. Interoperability between BIM and energy simulation is currently a challenge, with many approaches that claim to transfer between software. In practice, these processes are unsatisfactory unless the BIM model is extremely simple and ‘clean’. Therefore, for this case study a separate energy model was created in the DesignBuilder software, which uses EnergyPlus as a simulation engine. The various floor plans and elevations were exported from Revit which allowed a simple and quick model creation in DesignBuilder. A 3D representation of the building geometry modelled in DesignBuilder is shown in Figure 4.4.

In addition to the raw geometry, a building energy model requires significant additional, contextual, semantic information. This included construction material properties such as thickness and thermal conductivity, occupancy profiles of each zone, lighting and electronic equipment sizes and operational schedules. This information was gathered through a combination of a building survey and questioning the building occupants. The building is naturally ventilated and cooled, and for the purposes of this experiment, an electrical heating system was modelled with separate zone thermostat controls assumed. In this study, day by day occupancy prediction has not been considered. Instead, the same occupancy patterns have been modelled for each working day based on average building use. Whilst the occupancy patterns do not change from day to day, different zones were modelled with different occupancy patterns based on their use criteria. It was assumed that the 3 office zones and the reception area is occupied from 08:00 until 19:00. The kitchen is occupied from 12:00 until 14:00 and the meeting room from 10:00 to 11:00. If deployed in reality, the meeting room occupancy patterns could be retrieved from the electronic booking system used for this zone. Due to a lack of real building data, particularly in relation to the energy consumption of the building as a whole and each individual room, the generated energy model could not be validated. Throughout the rest of this section the DesignBuilder model of the office building is assumed

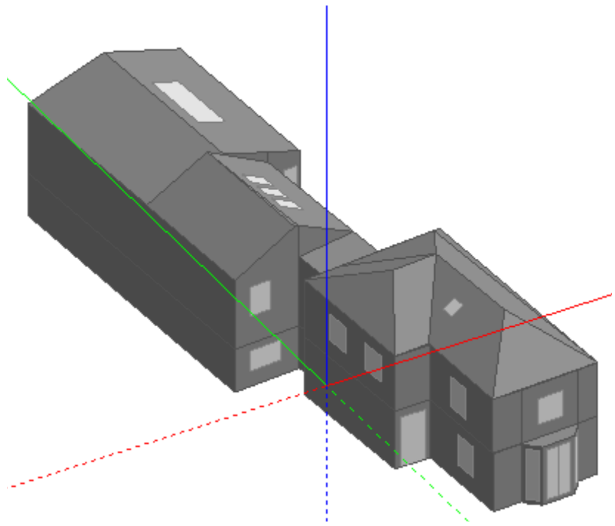


Figure 4.4: Design Builder model of the case study building

to be representative of the building and will provide the baseline against which the optimal control strategy will be compared.

4.2.4 Modelling Using an Artificial Neural Network

For the optimisation utilised in this chapter, it was necessary to be able to predict the heating energy consumption and the indoor temperature of each conditioned zone, at each hour of the day for the entire 24-hour time horizon. This calculation needed to be completed quickly and efficiently to be combined with a GA optimisation strategy. Therefore, the full energy simulation could not be used as an evaluation engine. Hence, an ANN surrogate model for each zone was trained using the simulation data produced by the previously described energy model so it could accurately replicate it during the real-time optimisation.

4.2.4.1 Data Generation

To generate the training dataset for the ANN, the model was run several times with varying set point schedules to generate a large training dataset. It is not possible to cover every combination of heating set point schedules due to the fact there are 24 decision variables each with a range of 12°C . Therefore, the aim was to produce a training dataset which adequately covered the possible solution space to allow the ANN models to generalise the relationship between inputs and outputs. To achieve this, a different heating set point schedule was used for each zone, each month, during each separate simulation. The model was run from the 1st of January to the 31st of March to cover the heating period in which the optimisation will be tested. So, for a single 3-month simulation of

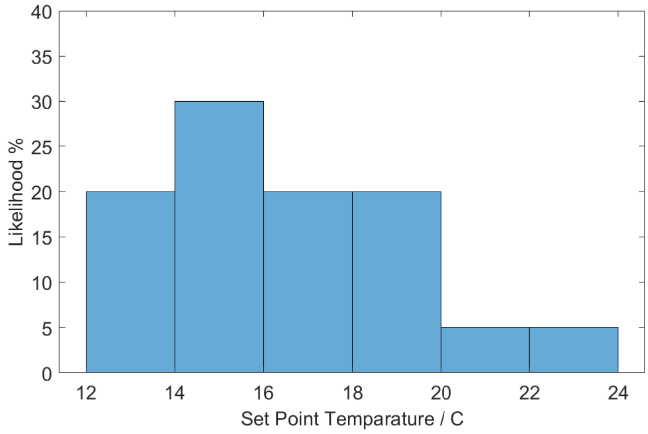


Figure 4.5: Probability distribution of heating set point temperatures during unoccupied hours

the case study building with 6 zones, 18 unique heating set point schedules were used.

To make the creation of these training simulations reproducible and relatively automated, a procedural methodology was used to generate the entire dataset. The methodology to generate the random heating set point schedules was based on an assumption that during the unoccupied period the heating set point could take any value from 12°C to 24°C , and during occupied periods any value between 19°C and 24°C . However, the selection of the set point values within this range was not set entirely randomly. The training set point schedules were generated in such a way that different temperatures would have a different likelihood of being chosen. During the unoccupied period, the majority of the values would fall in a more 'typical' low range whilst a small probability would remain that high set point temperatures could be selected. The chosen probability distribution is shown in Figure 4.5, for example there is a 30% chance that the heating set point temperature at any unoccupied hour will be between 14°C and 16°C , whilst there is only a 5% chance that a value between 22°C and 24°C would be chosen.

This generation of set point schedules aims to strike a balance between coverage of the entire solution space yet an increased coverage density over more 'sensible' set point values that the optimisation is expected to choose more frequently. During occupied hours, the possible temperature range is much reduced and therefore there was an equal chance of any temperature between 19°C and 24°C being selected. To illustrate this procedure, Figure 4.6, shows ten, 24-hour, heating temperature set points generated using this method.

The simulations were carried out for the three months of January through

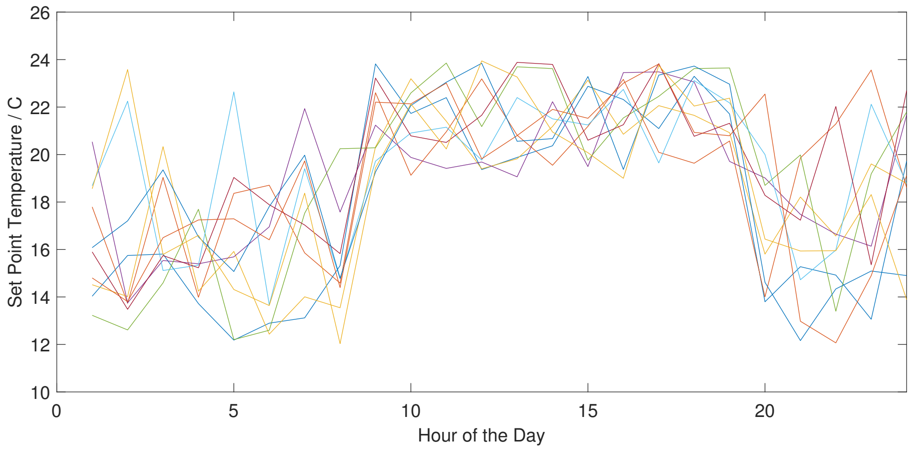


Figure 4.6: A sample of ten heating set point temperature profiles generated using the described methodology

to March. This period is expected to have high heating demand and should give a representative heating profiles throughout the winter period which will be the only period considered in this optimisation case study. Note that the ANN prediction models would need to be retrained if they were required for use in other seasons. In total, ten, three-month simulations were carried out to produce the training dataset. Therefore, each zone has 30 unique heating set point schedules.

The testing dataset, by which the ANN's performance will be assessed, is produced using the same method of generating diverse heating set point schedules. However, to provide a more meaningful test, the simulations will be carried out over the same months but using a weather file from the following year. This allows a more thorough assessment of the generalisation capability of the prediction models. The total size of the dataset provided from training and validation is 21830 hourly samples whilst the testing dataset is comprised of 4318 hourly samples.

4.2.4.2 ANN Configuration

The aim of the ANN is to accurately replicate the calculation of zone-level energy consumption and indoor temperature over the next 24-hours. A range of potential variables were considered as inputs to these ANN with the criteria that they must be known 24-hours in advance to allow prediction over the whole optimisation horizon. The possible variables considered as potential inputs to the ANN included the weather variables of outdoor dry-bulb temperature, relative humidity and solar radiation. It is theorised that these variables could reasonably be retrieved from local weather services with high forecasting accuracy.

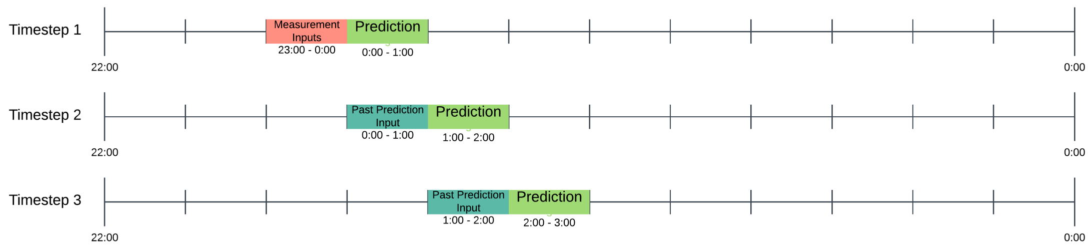


Figure 4.7: The process of predicting temperature using previous hourly temperature as inputs at different timesteps

Additional variables were related to time and date such as the month, the day of the month, the hour of the day and the day type (1 to 7 representing the days of the week, 1 is Sunday). The occupancy of the zone was represented as a binary variable, 1 for occupied, 0 for unoccupied. Finally, given that the thermal inertia of a building is a considerable factor, the indoor temperature from the previous timestep was also considered as an input. However, as the requirement is to predict for the next 24 hours, the prediction of indoor temperature at time t is used as the input to predict at time $t + 1$. These predictions are rolled over until the full 24-hour time horizon has been completed. For example, the prediction of the indoor temperature at timestep one would use the measured indoor temperature from the previous hour. Once predicted, the value of indoor temperature from timestep one would be used as the input to predict timestep two. This procedure is represented for different timesteps in Figure 4.7.

All ANN described in this section and throughout this thesis were trained using the Matlab Neural Network Toolbox (now named the Deep Learning Toolbox). As explained in Section 3.4.1, the term ANN encompasses a growing range of distinct machine learning models. For clarity, when the term ANN is used here, it is referring to a backpropagation neural network. There are several controllable parameters to consider when training an ANN. These include the training function, input variables, number of hidden neurons, and transfer functions. In this work, a stepwise searching method was used to find the optimal configuration of the ANN for each zone to predict the indoor temperature and the energy consumption every hour depending on the heating set point temperature and the other uncontrollable variables described above. From the authors experience and evidenced by MATLAB's ANN toolbox recommendations, the Levenberg-Marquardt training algorithm was the only training algorithm considered in this study. All considered ANN contain two layers of hidden neurons which can contain 5, 10, 15, or 20 neurons in each layer. The transfer function between in the input layer and the first hidden layer as well as the transfer function between the first and second hidden layer could be the hy-

Table 4.1: Energy prediction performance of the Researcher Office ANN with varying configurations

ANN Number	Inputs Selected										Hidden Neurons		Transfer Function		R^2 Results	
	1	2	3	4	5	6	7	8	9	10	Layer 1	Layer 2	Layer 1	Layer 2	Train	Test
1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	15	15	tansig	tansig	0.9885	0.9725
2	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	15	15	tansig	tansig	0.9858	0.9726
3	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	15	15	tansig	tansig	0.9833	0.9747
4	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	15	15	tansig	tansig	0.9806	0.8981
5	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	15	15	tansig	tansig	0.9907	0.9709
6	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	15	15	tansig	tansig	0.9910	0.9717
7	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	15	15	tansig	tansig	0.9898	0.9698
8	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	15	15	tansig	tansig	0.9608	0.9326
9	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	15	15	tansig	tansig	0.9806	0.9770
10	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	5	5	tansig	tansig	0.9641	0.9601
11	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	10	tansig	tansig	0.9778	0.9767
12	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	15	tansig	tansig	0.9789	0.9768
13	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	15	10	tansig	tansig	0.9798	0.9761
14	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	20	tansig	tansig	0.9793	0.9759
15	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	20	10	tansig	tansig	0.9814	0.9758
16	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	20	20	tansig	tansig	0.9826	0.9755
17	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	15	15	tansig	logsig	0.9802	0.9768
18	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	15	15	logsig	tansig	0.9810	0.9766
19	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	15	15	logsig	logsig	0.9801	0.9765

Note - Input numbers represent: 1-Month, 2-Day of the month, 3-Hour of day, 4-Outdoor temperature, 5-Relative humidity, 6-Solar radiation, 7-Day type, 8-Occupancy, 9-Set point temperature, 10-Indoor temperature at previous hour

perbolic tangent sigmoid transfer function ('tansig') or the Log-sigmoid transfer function ('logsig').

For the sake of both clarity and brevity the procedure to determine the configuration of just a single ANN, relating to a single zone, will be discussed here. The ANN in question aims to predict the energy consumption of the Researcher's Office in the case study building. This should illustrate the general procedure used to determine the ANN architecture and the same principles have been used to produce every other ANN, the results of which will be summarised at the end of this section. In all cases the determining objective by which ANN quality will be judged is the coefficient of determination (R^2) between the target EnergyPlus output and the ANN model prediction based on the testing dataset. For discussion purposes the R^2 value measured based on the training data is also provided. For each ANN configuration, the model was trained 5 times independently. Each time the model is trained the network is initialised with random weights and biases, this leads to slightly different ANN performance each time. The results of each configuration given in Table 4.1, show the results of the best of the 5 ANN training runs.

The first 9 entries of Table 4.1 aim to find the optimal combination of inputs that produce the best results for predicting energy consumption on the testing dataset. Initially, the model was generated using all possible inputs and then different inputs were removed sequentially to assess their importance. During this stage, the other ANN parameters such as transfer function and number of neurons in each hidden layer remained constant. It was found that removing month and day of the month (ANN 2 and 3) as inputs improved prediction performance. The removal of relative humidity and solar radiation (ANN 5 and 6) had little impact on the prediction performance. The removal of occupancy, previous temperature and in particular day type (ANN 7, 8 and 4) significantly worsened ANN prediction accuracy. Finally, the performance of ANN 9, which removed the month, day of the month and relative humidity provided the best prediction performance of the input combinations tested. From this point onwards, the ANN inputs remained constant and focus turned to refining the remaining ANN parameters.

Next, the number of neurons in each hidden layer was altered ranging from as low as 5 neurons to as high as 20 neurons. ANN 10 to 16 show that reducing the number of neurons in the hidden layers generally reduces the gap between the training performance and the testing performance. This is possible evidence that the higher numbers of neurons lead to a higher degree of overfitting. Overfitting occurs when the ANN too closely learns the training dataset without generalising the relationships between inputs and outputs. Then, when applied to a new dataset, a significant drop in performance is observed. Providing the number of neurons is above 5, prediction accuracy on the testing dataset remained consistent. However, in this case, the best testing results were achieved by ANN 9 with 15 neurons in each hidden layer. Finally, the transfer function between the input layer and the first hidden layer, and the transfer function between the two hidden layers was assessed. With the inputs and number of neurons remaining constant, altering the transfer functions between tansig and logsig resulted in very little change in prediction performance. The best R^2 value when applied to the testing dataset was achieved with two tansig transfer functions, hence the final ANN architecture was chosen to be that of ANN 9.

After following the procedure described above, the final configurations of all zones energy prediction ANN as well as the ANN that predicts the whole building energy consumption is shown in Table 4.2. A similar table that displays the performance of the temperature prediction ANN is found in Table 4.3. Regarding the energy consumption ANN, a small drop in performance is noticeable from training to testing. In each case the drop in performance ranges from 0.01 to 0.02. The modest size of this performance deterioration indicates that the ANN have been able to generalise the relationship between inputs and outputs with little sign of overfitting. The temperature prediction ANN demonstrate

Table 4.2: Final configuration and performance of the energy prediction ANN

Zone	Inputs Selected										Hidden Neurons		Transfer Function		R^2 Results	
	1	2	3	4	5	6	7	8	9	10	Layer 1	Layer 2	Layer 1	Layer 2	Train	Test
1	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	20	10	tansig	tansig	0.9514	0.9365
2	✗	✓	✓	✓	✗	✓	✓	✓	✓	✓	15	10	tansig	tansig	0.9919	0.9767
3	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	15	15	logsig	tansig	0.9731	0.9667
4	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	10	tansig	tansig	0.9804	0.9739
5	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	10	15	tansig	tansig	0.9769	0.9523
6	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	15	15	tansig	tansig	0.9806	0.9770
All	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	15	tansig	tansig	0.9683	0.9561

Note - Input numbers represent: 1-Month, 2-Day of the month, 3-Hour of day, 4-Outdoor temperature, 5-Relative humidity, 6-Solar radiation, 7-Day type, 8-Occupancy, 9-Set point temperature, 10-Indoor temperature at previous hour

Table 4.3: Final configuration and performance of the indoor temperature prediction ANN

Zone	Inputs Selected										Hidden Neurons		Transfer Function		R^2 Results	
	1	2	3	4	5	6	7	8	9	10	Layer 1	Layer 2	Layer 1	Layer 2	Train	Test
1	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	15	tansig	tansig	0.9911	0.9859
2	✗	✓	✓	✓	✗	✓	✓	✓	✓	✓	10	15	tansig	tansig	0.9971	0.9960
3	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	10	tansig	tansig	0.9968	0.9961
4	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	20	10	tansig	tansig	0.9982	0.9970
5	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	10	10	tansig	tansig	0.9968	0.9945
6	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	15	tansig	logsig	0.9966	0.9961
All	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	10	15	tansig	logsig	0.9966	0.9961

Note - Input numbers represent: 1-Month, 2-Day of the month, 3-Hour of day, 4-Outdoor temperature, 5-Relative humidity, 6-Solar radiation, 7-Day type, 8-Occupancy, 9-Set point temperature, 10-Indoor temperature at previous hour
Zone Numbers: 1-Downstairs Office, 2-Kitchen, 3-Reception, 4-Meeting Room, 5-PhD Office, 6-Researchers Office

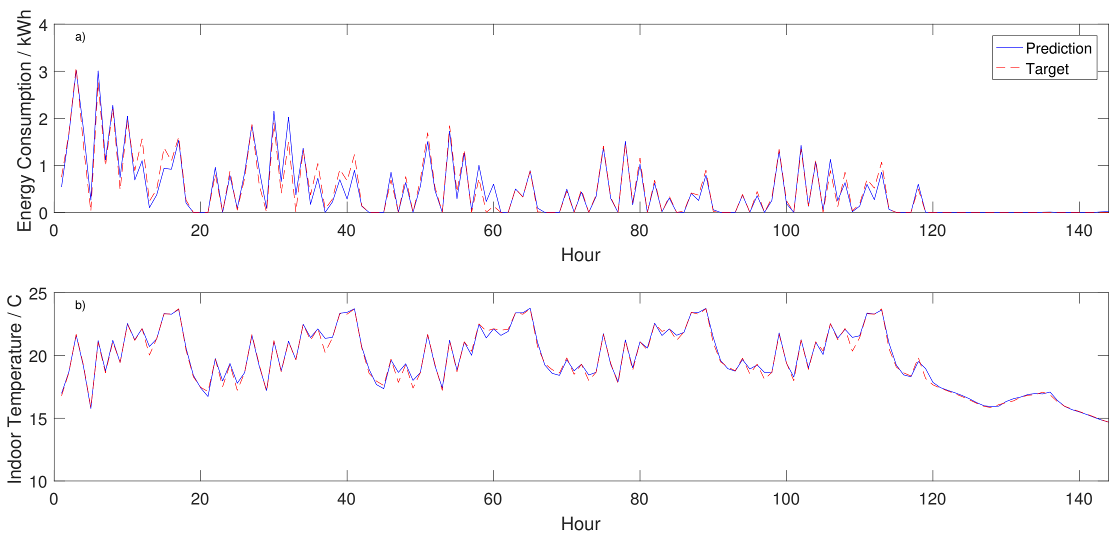


Figure 4.8: Sample prediction of a test week of the Downstairs Office for a) Energy consumption, b) Indoor temperature

an even smaller drop in prediction accuracy than the energy ANN. Across all zones (and the whole building ANN), the optimal combination of inputs is reasonably consistent with 5 out of the 7 having an identical set of inputs. The indoor temperature prediction performance is consistently higher than their energy prediction counterparts. However, the poorer statistical performance of the energy prediction ANN is partly due to the nature of the data. Heating energy consumption is much more 'spiky' in nature with a few, large peaks but an overall low mean. This is significantly harder to predict than the gradual evolution of indoor temperature. Furthermore, during the testing procedure, the inputs assume a perfectly predicted indoor temperature from the previous hour. In reality, this value will be iterated over several times causing a propagation in error. It is expected this will have a greater impact on the indoor temperature prediction as it has a greater correlation with the previous indoor temperature than energy consumption. To demonstrate the accuracy of the ANN in a more visual way, the ANN prediction of energy consumption and indoor temperature by the statistically worst zone (zone 1) has been plot over a sample test week in Figure 4.8.

4.3 Optimisation Strategy

As mentioned in the previous section, a GA is used to optimise each zone's set point temperature for the next 24 hours. This section will provide finer detail of the optimisation process. The general GA theory and procedure is provided in Section 3.4.2 and will not be repeated in full here. Only the implementation of the GA in the context of this optimisation problem will be discussed. In this scenario the each individual within the GA population has 24 chromosomes which represent the set point temperature of a zone at each hour of the day. These decision variables have a lower bound of 12°C and an upper bound of 24°C . The exact parameters of the GA used in this case study is shown in Table 4.4. Note that the maximum number of generations is set to the MATLAB default of 100 multiplied by the number of decision variables which in this instance is relatively high. This allows the GA to exit in all cases by reaching the function tolerance which ensures that the GA has fully converged rather than forced to exit prematurely.

4.3.1 Objective Function and Fitness Evaluation

The objective of this optimisation strategy is to minimise the energy consumption whilst maintaining thermal comfort by selecting the optimal temperature set point schedule, each hour, for each zone. The set point is free to vary

Table 4.4: Genetic algorithm parameter settings

GA Parameter	Value
Number of Variables	24
Population Size	200
Creation Function	Uniform
Selection Function	Tournament
Crossover Function	Scattered
Crossover Fraction	80%
Mutation Function	Uniform
Mutation Rate	0.1
Elite Count	5%
Maximum Number of Generations	2400
Function Tolerance	1×10^{-5}

between 12°C and 24°C during unoccupied periods and 20°C to 24°C during occupied times as these were the temperature bounds requested by the occupants to maintain thermal comfort. Whilst the setting of these bounds forms a large part of ensuring thermal comfort is met a further internal penalty function is included. If the indoor temperature predicted by the ANN is below 20°C or greater than 24°C when the zone is occupied, then the energy consumption during that timestep is set at 100kWh. This very harsh penalty effectively excludes that solution from being competitive in the fitness evaluation and hence the solution which breaches comfort constraints will not be selected. This penalty function is mainly necessary during the first occupied hour of the day where it is conceivable that the zone set point temperature would be above the lower bound of 20°C but the indoor temperature would remain lower than this during the first hour as the zone warms up.

The fitness evaluation procedure developed in this Section is displayed in Figure 4.9. The relevant input variables for each zone are retrieved and combined into one matrix with the appropriate structure to be provided as an input to the ANN. These include the outdoor temperature, solar irradiance, hour of the day, occupancy, temperature set point and previous indoor temperature. Once the inputs are collated, they are fed to the zone ANN which predicts energy consumption and indoor temperature for that timestep. Then follows the thermal comfort check to ensure that during occupied hours the indoor temperature is predicted to be above 20°C and below 24°C . If this is not the case the energy consumption for that time step is changed to 100kWh. Unless all 24 hours have been calculated, the process loops around to repeat the calculation for the next timestep using the internal temperature prediction from the previous hour as an input. Once all 24 hours have been completed, the energy

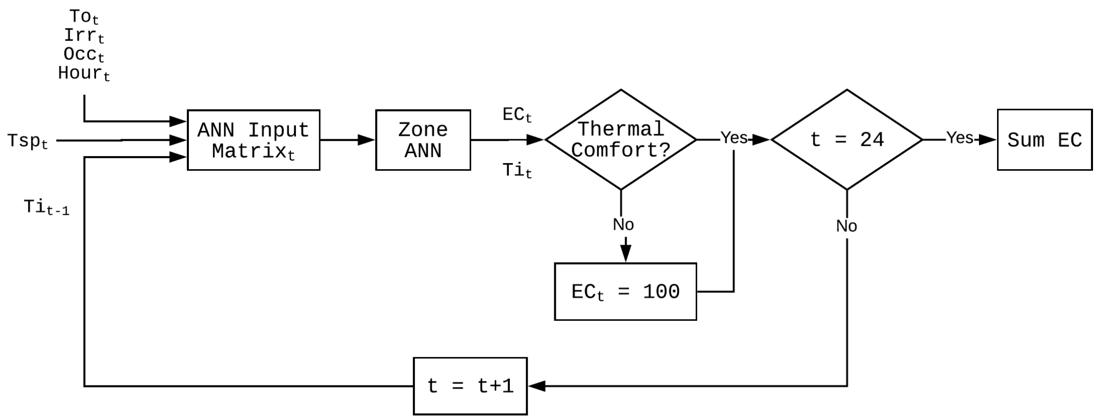


Figure 4.9: Flowchart of the fitness evaluation procedure for a single zone (t-Timestep, To-Outdoor Temperature, Irr-Solar Irradiation, Occ-Occupancy, Tsp-Set Point Temperature, Ti- Indoor Temperature, Ec-Energy Consumption)

consumption is summed over the 24 hours and the resulting number is the solutions fitness. A GA using the described procedure is completed for all 6 conditioned zones. This procedure can be accomplished in parallel to reduce optimisation time as each zone optimisation is independent and not reliant on inputs from other zones. For the case of the whole building optimisation, the procedure is identical but instead of 6 parallel optimisations for each zone, only one building-level optimisation is required and the decision variable is the building set point temperature.

4.3.2 MPC Adaptations

The optimisation procedure described in the previous sub-section can be run once at midnight and produce a schedule for the following day provided it has 24-hour weather and occupancy predictions and the initial zone temperatures. In this study, the effect of implementing this strategy as MPC will also be assessed. When implemented 24-hours ahead without MPC, errors in temperature prediction at earlier timesteps can lead to compound errors later in the day. Once set, the entire heating set point schedule would be enacted regardless of any unforeseen changes in circumstances. However, if implemented as MPC, the optimisation would be run every hour, still with a 24-hour time horizon. This would allow feedback of the internal temperatures from the building control system, allowing the controller to react to any prediction errors or receive a more up-to-date weather forecast. Running as MPC means the 24-hour set point schedule is updated and changed every hour but only the first hour of each optimisation is ever enacted.

As this is a simulation based case study, the ‘real’ building is replicated by an EnergyPlus simulation model, thus a method of automatically linking the EnergyPlus model and the MATLAB optimisation procedure was required. The Building Controls Virtual Test Bed, BCVTB [37], middleware software was used to achieve this. The BCVTB model has two main 'actors', namely these are the MATLAB simulator and the EnergyPlus building simulator. The BCVTB interface is shown in Figure 4.10. Each variable is represented by a line between the actors, in addition BCVTB can produce a collection of timeseries plots for the users' benefit. In this case the indoor temperature alongside the set point temperature of each zone is plotted in addition to the overall electricity consumption. The data interchange, facilitated by BCVTB, was configured to allow retrieval of each zone's indoor temperature every 10 minutes. On the hour, the average indoor temperature of each zone was calculated. This provided the starting point for the optimisation to run. Using these initial values, the optimisation procedure could generate a 24-hour set point schedule for each zone. The first value of the optimal set point schedules was returned to BCVTB to be implemented within the EnergyPlus model for the following hour. Once this hour was complete the temperature was again recorded by BCVTB, passed to MATLAB and the optimisation is run again with the updated, 'real', temperatures from the building. Note that the optimisation procedure that takes place each hour is identical to that described in Section 4.3.1, however it occurs 24 times a day rather than just once at the beginning of each day. If deployed in reality, instead of using the EnergyPlus simulation model, you would simply record the measured indoor temperature in each zone before carrying out the optimisation. In the case of the whole building optimisation, the interaction with BCVTB is identical, however only one set point value is provided and it is implemented in all zones. The general procedure is displayed in the diagram shown in Figure 4.11.

4.4 Results

In this section the GA-ANN, zone level, heating set point scheduler will be applied during a test week in February using actual, 2016, weather data from a nearby weather station in Cardiff which was converted to an epw file for use in EnergyPlus. To provide a comparison, a baseline scenario has also been developed. This uses a typical heating set point strategy which is 21°C during the occupied hours (08:00 to 19:00) and 12°C during unoccupied hours in all 6 conditioned zones. The optimisation will be run as day ahead scheduling and then as MPC with a 1-hour timestep and 24-hour control horizon. Note that in both cases the schedules resulting from the optimisation will be put

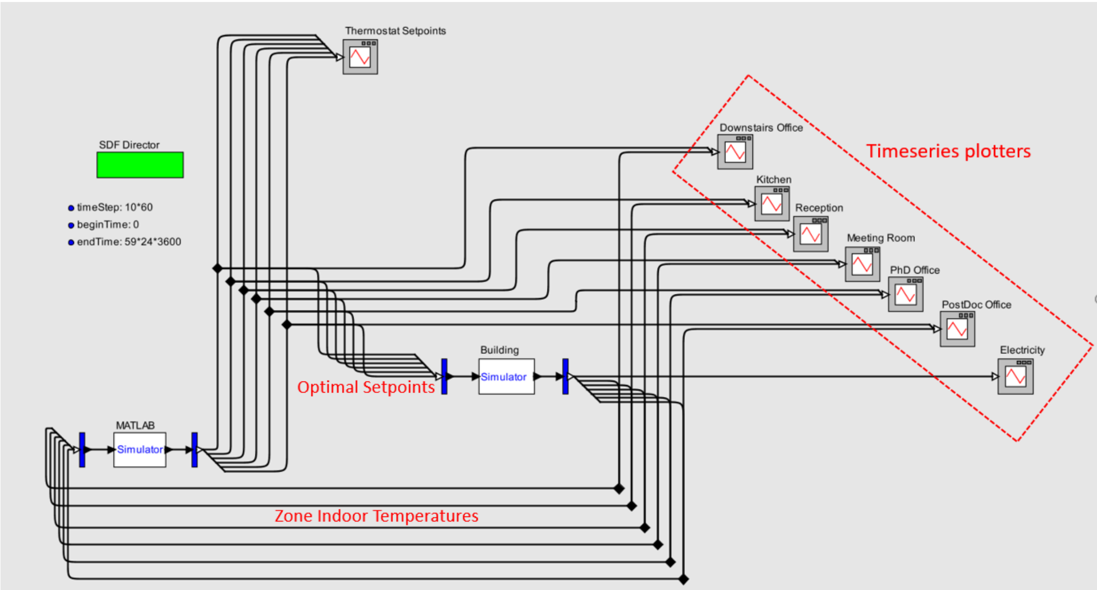


Figure 4.10: BCVTB user interface showing data exchange connections between MATLAB and EnergyPlus

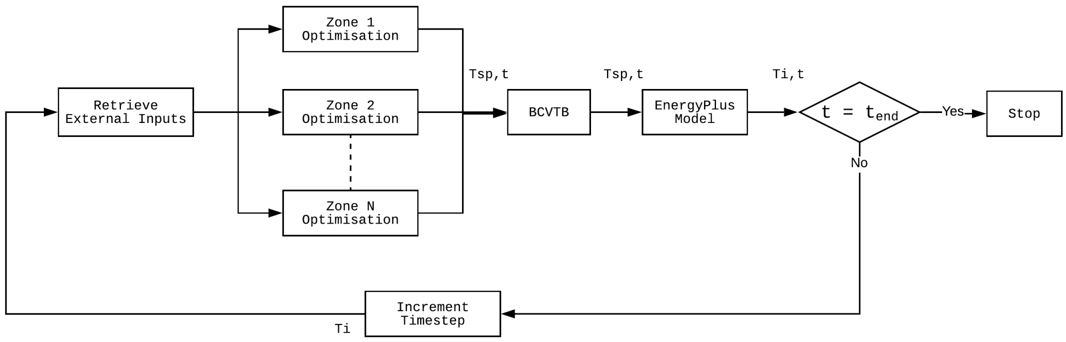


Figure 4.11: Optimisation procedure in MPC format integrated with BCVTB

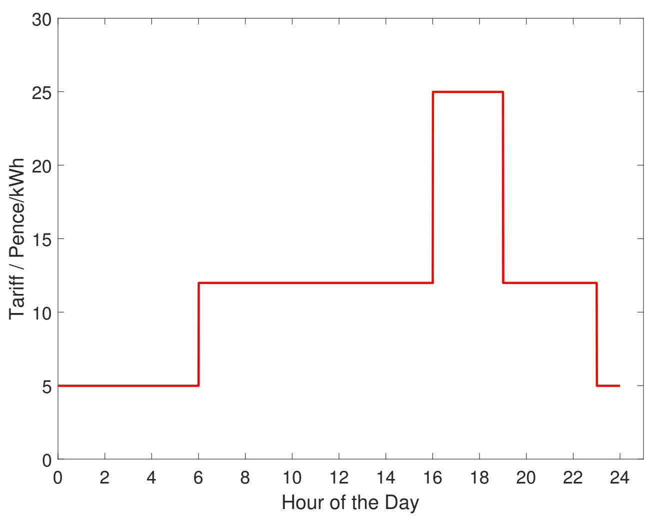


Figure 4.12: TIDE tariff electricity price on weekdays

back into EnergyPlus to validate the results. This allows fair comparison with the baseline scenario as all simulation models are identical (including weather conditions) apart from the heating set point schedule of the zones. This also removes any influence ANN prediction errors may have to allow true evaluation of the effect of the optimised set point strategy.

Initially, a comparison will be made between zone-level control against whole building control. In the whole building control case, the optimisation will be run as described previously using the ANN that model the whole building energy consumption and the weighted average building temperature. This optimisation produces a heating set point schedule that is applied to all building zones. Note that the optimisation will be run in day-ahead mode and using a flat energy pricing tariff during this comparison. Once an assessment of zone-level vs building level optimisation has been made, a second scenario using a ToU tariff will be introduced. In the initial scenario, minimisation of energy consumption also minimises energy cost as there is a constant electricity price. In the second scenario, the TIDE tariff from Green Energy UK [329], shown in Figure 4.12 is used. Energy is cheapest, £0.0499/kWh, from 23:00 to 06:00 and has peak prices of £0.2499/kWh between 16:00 and 19:00, all other hours are an intermediate price of £0.1199/kWh. In this scenario the optimisation is adjusted to minimise the energy cost incurred to maintain a comfortable building. This is achieved very simply by altering the fitness function to multiply the energy consumed by the tariff price at each hour and the fitness is the sum of the energy costs over the 24 hour period. In both pricing scenarios, the optimisation will run as both day ahead optimisation and MPC. In all cases the optimisation is run over the week of the 15th to the 19th of February 2016 (note that the optimisation is not run on weekends).

4.4.1 Building-Level vs Zone-Level Control

The energy consumption of each zone in addition to the sum total for the baseline scenario, building-level optimisation and the zone-level optimisation is shown in Figure 4.13. In this case the optimisation was run as day-ahead and using a flat energy tariff. The building-level optimisation achieves a 10% reduction in energy consumption compared to the baseline strategy whilst the zone-level optimisation achieves an 18% reduction in energy consumption. The significant gains made by the zone-level optimiser compared to the building-level optimiser are found in zones 2 and 4. These zones are the kitchen and the meeting room respectively and are only occupied for a couple of hours per day. Clearly, the zone-level optimisation can take advantage of this situation

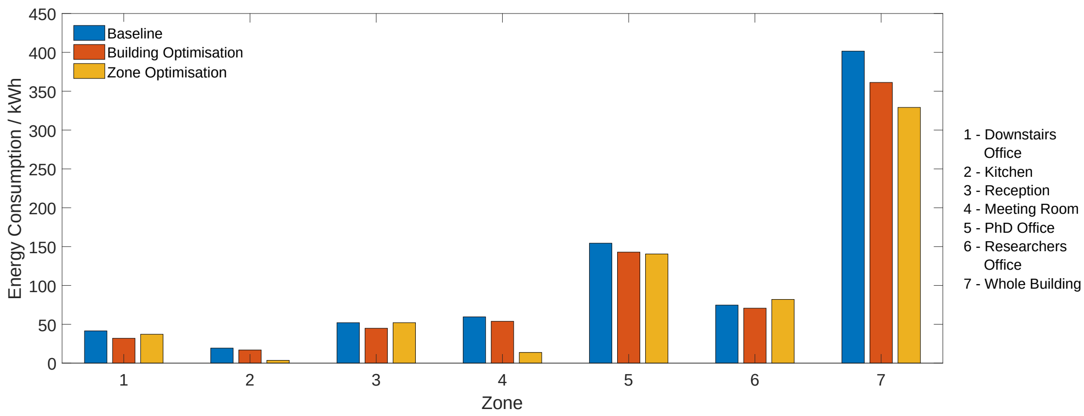


Figure 4.13: Energy consumption of each zone and the sum total when using the baseline, building-level and zone-level strategies.

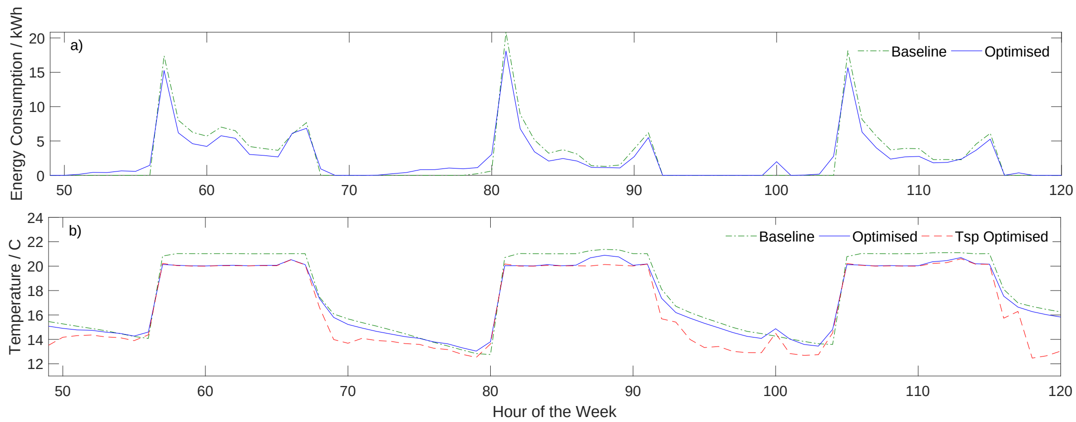


Figure 4.14: Result of the building level optimisation over 3 sample days compared to the baseline scenario: a) Energy consumption, b) Indoor temperature

and only needs to maintain these zone temperatures during their occupied periods. The building-level optimisation cannot make these decisions as it can only set one heating set point schedule for the entire building. Also of note, the zone-level optimisation actually results in an increase in energy consumption for zones 3 and 6 compared to the baseline and building-level optimisation. These zones, the reception and researchers office, are directly adjacent to the meeting room. So the minor increase in energy consumption is not a failure of the optimisation, rather a reflection of the heat losses from these zones to the comparatively colder meeting room.

To assess how the building-level optimisation has achieved energy savings, the energy consumption, indoor temperature and set point temperature during the optimised and baseline scenario have been plot in Figure 4.14. To strike a compromise between illustrating as much of the results as possible and ensuring legibility, three of the optimised days will are shown throughout this Chapter. Whilst the optimisation strategy does make a small effort to more gradually pre-heat the building during the mornings, the majority of the energy savings come by simply lowering the set point temperature to the lower bound of 20°C . This rather blunt method of reducing energy consumption is due to the optimisation having to balance the requirements of each zone within just a single building-level set point. It does not have the fine level of granularity to make more bespoke decisions for the control of indoor temperature. It is not possible to provide a fair comparable graph of the zone-level optimisation performance here, as the unoccupied zones lower the weighted average building temperature. Illustration of the performance of the zone-level optimisation will continue in the following sections.

4.4.2 Standard Energy Tariff

Having demonstrated the potential benefits of zone-level temperature control over building-level optimisation, this section will explore the decisions made by the zone-level controller and provide comparison between the optimisation running as day ahead optimisation or as MPC. Throughout this subsection, the standard energy tariff is used in which the cost of electricity is constant. The energy consumption of each zone resulting from the day ahead optimisation and the MPC optimisation is shown in Figure 4.15. There is a very minor difference between the day ahead optimisation and the MPC across all zones. In fact, the day ahead optimisation slightly outperforms the MPC. Both optimisations show the potential for around 18% energy savings over the course of this test week. As previously discussed, a major source of the energy savings come from the kitchen and the meeting room which are sporadically occupied but are currently heated all day reflected in the baseline scenario. However, there are also energy savings from some of the office zones despite having the same 08:00-19:00 occupied period.

To understand these savings, Figure 4.16 shows the set point schedule, indoor temperature and energy consumption of Zone 1 (the downstairs office) during the day ahead optimisation. Once again, it is evident that the optimisation chooses a more gradual warming up period than the baseline scenario with some pre-heating before 8am. In contrast to the building-level optimisation, the optimisation chooses to increase the zone temperature in the afternoon to coincide with the increased solar gain to this zone. The combination of these measures reduce the early morning and late afternoon energy peaks. Whilst the average occupied temperature is below that of the baseline average temperatures, the optimised solution does remain within the comfort boundaries requested by users and maintains a higher average temperature than the building-level optimisation. In summary, both optimisation modes (day-ahead

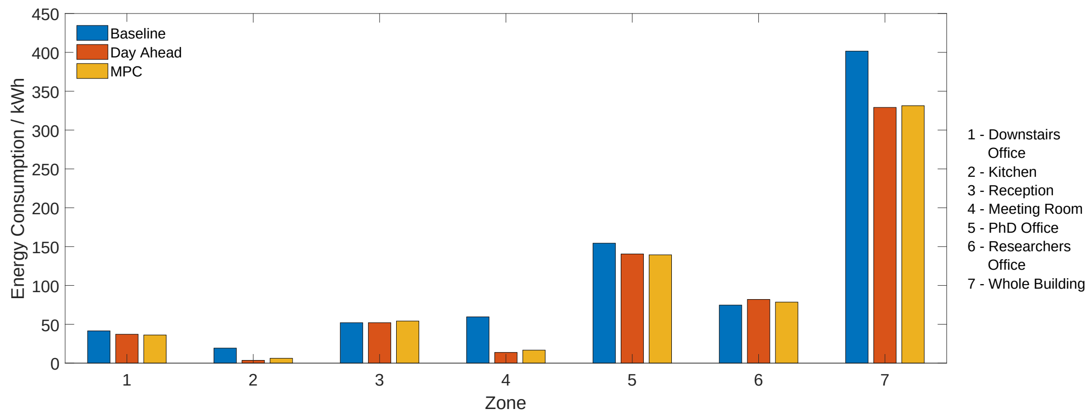


Figure 4.15: Energy consumption of each zone and the total using the baseline, day ahead optimisation and MPC strategies with a standard energy tariff.

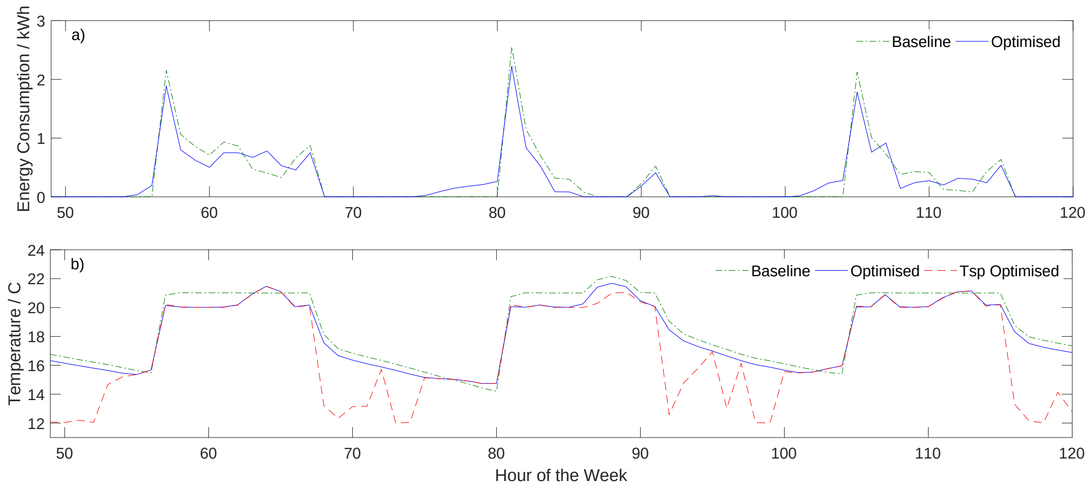


Figure 4.16: Result of the zone-level optimisation on Zone 1 over 3 days compared to the baseline scenario: a) Energy consumption, b) Indoor temperature

and MPC) have shown significant energy savings can be made by allowing a smart scheduler to have the freedom to vary set point temperatures between pre-defined bounds and by actively considering occupancy and weather conditions. However, it has not demonstrated the value of MPC over day ahead scheduling in this scenario.

4.4.3 Time of Use Tariff

To assess the flexibility of the proposed energy management procedure, both the day ahead optimisation and the MPC optimisation were run again using the the TIDE ToU tariff outlined earlier in this section. The same week was studied using identical weather conditions. The same baseline scenario is used which cannot make any attempt to adjust to the new pricing regime as it is static. When optimising using the ToU tariff, the optimisation objective is altered to cost. Hence, Figure 4.17 shows the cost of heating energy incurred by each zone and the building as a whole for both optimisation modes and the baseline scenario. When optimising for cost, the percentage change compared to the baseline strategy grows to around 23.5% for both the day ahead and the MPC optimisation strategies. Once again there is very little to differentiate between the two optimisation modes with the day ahead optimisation marginally outperforming the MPC. Whilst minimisation of the energy consumption was not the objective in this scenario it is interesting to illustrate the energy consumption as shown in Figure 4.18. In comparison to the energy savings found in Section 4.4.2, the energy savings have decreased from around 18% to 15.5%. This shows that under a ToU tariff the minimisation of energy cost and energy consumption are not mutual.

To understand the new decisions that the optimisation makes when operating with a ToU tariff Figure 4.19 has been included. This figure illustrates the load shifting the optimisation attempts in order to shift energy consumption from the high price periods. The effort to pre-heat is much more pronounced with new peaks between 05:00 and 06:00 which is the last time period where the electricity price is at its lowest. Furthermore, there is some effort to increase the temperature during the late afternoon period to reduce the energy consumption during the on peak price period of 16:00-19:00 which it successfully achieves when compared to the baseline strategy. During the test week, both optimisation strategies were able to produce a saving of around £13 from the original baseline total of £54.40. Once again there was no clear difference between the day ahead optimisation and the MPC strategy.

4.5 Discussion

The results shown in Section 4.4.2 and Section 4.4.3 clearly indicate that implementing a smarter, more context aware building controller can lead to improvements over traditional static control. The consideration of additional semantic information such as predicted outdoor temperature, solar radiation and occupancy can give controllers greater scope to develop more bespoke strategies leading to reduced energy consumption and cost. This is evidenced by the 18% reduction in energy consumption with the standard energy tariff and a 23% reduction in cost with the ToU tariff. This Chapter has demonstrated that optimising at a zone-level rather than setting a building-level strategy can lead to additional savings in energy consumption. In this case study the zone-level optimisation made an additional 8% saving in energy consumption. The optimisation strategy was also proven to flexible to a changing energy environment. It

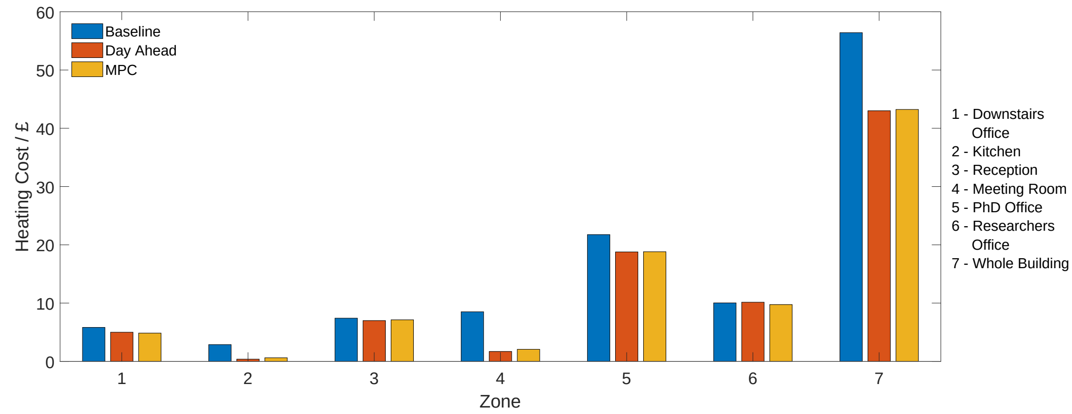


Figure 4.17: Heating energy cost of zones and the sum total when using the baseline, day ahead optimisation and MPC strategies with a ToU energy tariff.

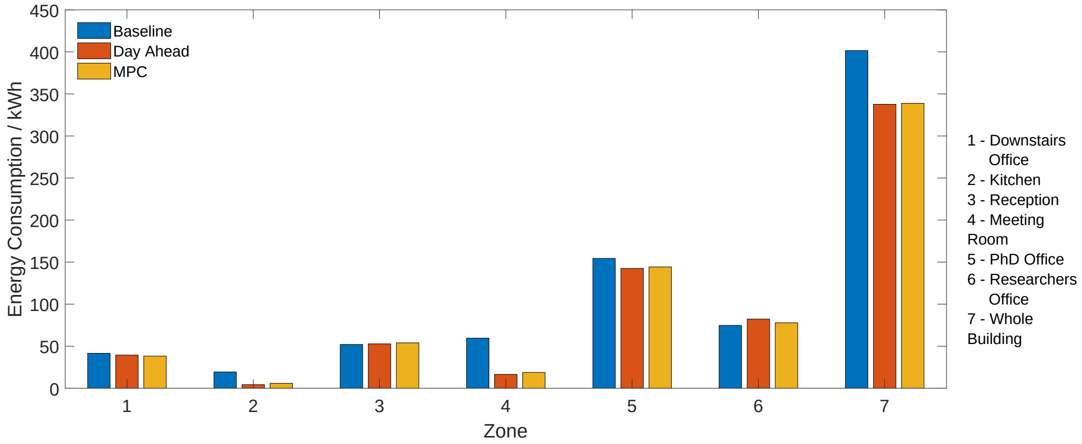


Figure 4.18: Energy consumption of zones and the sum total when using the baseline, day ahead optimisation and MPC strategies with a ToU energy tariff.

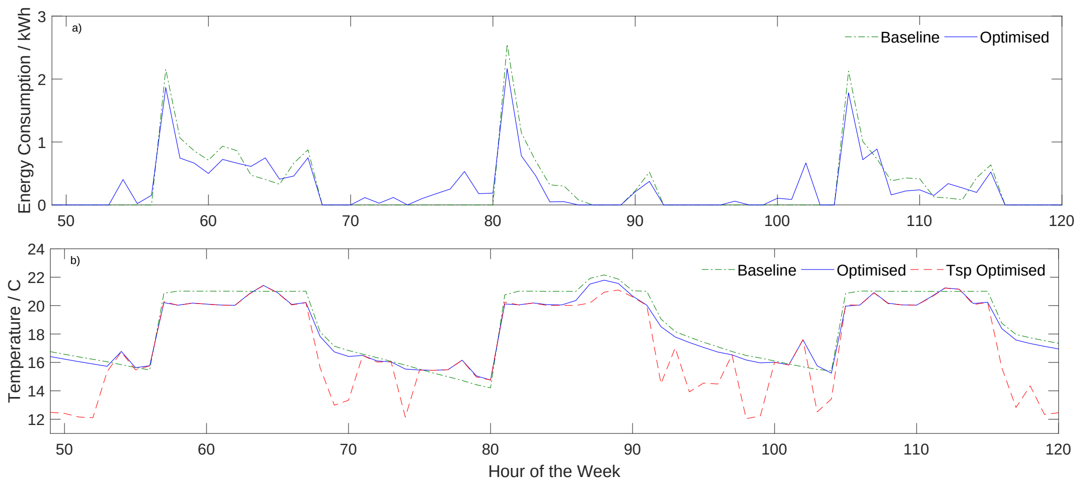


Figure 4.19: The result of the zone-level optimisation on Zone 1 with a ToU tariff compared to the baseline scenario: a) Energy consumption, b) Indoor temperature.

was simply adapted to take into account a ToU tariff and minimise energy cost rather than energy consumption. Further adjustments could simply be made to factor in local renewable resources or demand response events as part of a district heating network potentially benefitting the energy provider as well as the consumer.

The practical deployment of this solution to a real building would require a reasonably small amount of additional hardware. The optimisation procedure would require zone level temperature sensors and direct control of heating units. Currently, there is a significant surge in interest and availability of smart home devices controlled by a central AI coordinator using the paradigm of IoT. It is therefore feasible and indeed probable that most future (and some current) buildings, both commercial and residential, will have the capability to control individual room set points and devices through an integrated system. The proposed optimisation procedure would sit above these physical systems requesting and sending relevant information (set points and indoor temperatures) taking advantage of existing physical and network infrastructure. It is envisaged that this control scheme would be more applicable to commercial buildings initially. This is due to occupancy patterns being more clearly defined and predictable within office buildings and the fact that occupants do not necessarily expect to have direct control over the heating systems.

This particular case study has focussed on a single winter week to illustrate the performance of the proposed methodology. This week was specifically chosen to best demonstrate the actions of the controller as heat demand was high. However, the core concepts underpinning this controller could be applied to a wide range of building energy scenarios. In summer, it could control the cooling set point temperature to minimise cooling energy consumption. Also, the methodology could be adjusted to manage additional building comfort criteria such as ventilation and lighting. Provided an internal model can be produced that relates the decision variable to the objective and comfort constraints, this methodology can apply.

The ANN surrogate models developed in this paper have been proven to be accurate enough to replicate the simulation model in this case study. However, the most significant challenge in the application of this control strategy remains the development of the surrogate models for the prediction of energy consumption and indoor temperature. The approach used in this study was to train an ANN based on large amounts of simulated data. However, accurate simulation models are not widely available for most buildings. It is theorised that building simulation models are likely to become more available in the future, driven by government legislation aiming at reducing energy consumption from buildings and improving retrofitting procedures.

This is leading to increased prevalence of Building Information Modelling, BIM, which are increasingly including energy analysis modules. Researchers are working on methods to capture existing building information, convert to a digital representation, from which generate a building energy simulation model and calibrate the model based on existing historical data. Alternatively, if the case study in question has developed a significant log of historical energy consumption and temperature data, machine learning models could be directly generated from this. To model at an hourly or sub hourly temporal scale the authors' believe that specific ANN would be required for each building as generic ANN based on broader building categories would not be able to capture the intricacies if an individual building. Future work should aim to apply the modelling methods to a real case study building to validate the performance of this methodology. In addition the entire control strategy should also be implemented on a real building to demonstrate the true effectiveness of the methodology defined in this Chapter.

Throughout both tariff scenarios, the results show negligible difference between the day ahead optimisation and the MPC optimisation. This contradicts results published in many other state of the art building control papers. However, this may be due to the lack of uncertainty in the testing scenarios presented in this Chapter. Both occupancy and weather conditions are assumed known in advance and these forecasts are assumed 100% accurate which would not be true in practice. Therefore, future work should introduce forecasting uncertainty and assess the impact on the two optimisation scenarios. The hypothesis being that the MPC optimisation will adjust to these uncertainties better than the day ahead optimisation as updated, more accurate weather forecasts become available.

An additional point of future work will aim to create a mechanism by which each zones optimisation can influence adjacent zones. In this study, each zone is optimised separately. This was a conscious decision to allow each zone optimisation to run in parallel, hence reducing the total optimisation time to the order of 10 minutes. Despite the lack of interaction between the zone optimisations the proposed procedure was able to achieve significant energy savings with no loss to thermal comfort. This was likely due to the set point schedules not deviating significantly from day-to-day, the optimisation altered set points only marginally from the baseline. Therefore, the heat transfer from zone to zone did not vary to a degree that caused a significant enough impact to prevent the optimisation from working. Future work should aim to pre-screen case study buildings in order to assess closely coupled zones and develop a method by which decisions made in one zone are transmitted to the second.

4.6 Conclusion

This Chapter primarily aimed to answer research question 2:

Can predictive control of building energy demand with consideration of external factors lead to reductions in energy cost and improve demand-side flexibility?

The case study results clearly indicate that the outlined zone-level, building optimisation methodology significantly outperforms traditional rule-based, reactive control. The predictive and context-aware nature of the optimisation methodology led to clear energy savings and improvements over the baseline scenario. In addition to providing energy savings, this chapter has also demonstrated there is a degree of flexibility within building energy demand. The optimisation was altered to take into account an additional external factor, namely the ToU tariff. With this extra information, the optimisation successfully adjusted the building demand profile to best take advantage of the new scenario. This factor is a key foundation on which the remainder of the thesis will be built.

The original contributions resulting from the chapter are a combination of the following points:

- Zone level ANN have been developed to accurately forecast the indoor temperature and energy consumption by considering variable weather, occupancy and temperature set points.
- This is combined with a genetic algorithm to optimise the temperature set point to minimise either energy consumption or energy cost within a computationally short period.
- The effect of deploying the optimisation as day ahead optimisation or hourly, sliding window MPC was assessed.
- The control scheme was demonstrated to be adaptable to time varying energy prices.
- The zone-level optimisation reduced energy consumption by 18% and energy cost by 23.5% compared to the static baseline control scheme.

5 | District-Level Energy Management

The optimisation carried out in Chapter 4 focussed on a single building that was considered largely in isolation of any external energy networks (excluding pricing). However, as explored in Chapter 1 and Chapter 2, the energy sector is becoming increasingly devolved to local energy microgrids. Therefore, the next layer of research carried out in this thesis, focusses on the optimisation of the energy generation of a proposed district heating network. At its core, this chapter is driven by the following questions. In a multi-vector district energy system with several energy conversion technologies, how can the optimal operation of these technologies be determined? How can the resulting optimal schedule be adjusted to account for prediction uncertainties?

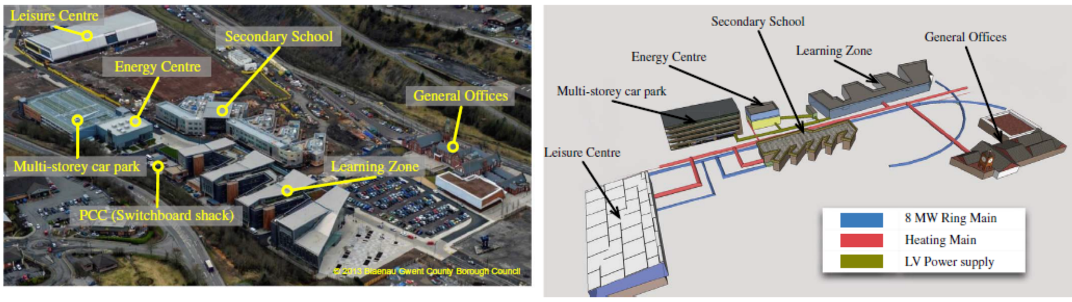
5.1 Revisiting the Research Question

This chapter aims to address research question 3, restated here as:

Can taking an optimisation-based approach to the control of district heat generation improve upon existing rule-based priority order strategies?

To tackle this question, a realistic, virtual eco-district has been developed. The optimisation strategy outlined in this chapter will aim to control the heat generation supply units and the thermal storage flexibility to maximise the operational profit to the district energy centre. To provide an appraisal of the optimisation performance, the results will be compared to a rule-based, priority order, baseline scenario similar to that used in existing pilot sites.

The methodology described in this chapter was originally published in the journal article, Reynolds et al. [330] and reformatted and expanded for this thesis. This work built upon the initial, proof of concept investigations conducted in Reynolds et al. [331].



(a) Aerial photo (b) Energy network topology

Figure 5.1: 'The Works' pilot site in Ebbw Vale [182]

5.2 Case Study District Description

The analysis carried out in this study is based on a virtual, simulated, eco-district containing mixed-use buildings alongside an energy centre producing heat, delivered by a district heating network. The district is designed to be based in the city of Cardiff, UK, with real historical weather files used as inputs to simulation models. This district has been inspired by the authors' involvement with real eco-districts, including "The Works" district in Ebbw Vale, Wales (UK) [283] through the RESILIENT and PENTAGON projects. Throughout these projects, significant modelling efforts have been undertaken when studying this pilot site illustrated in Figure 5.1. The entire district was scanned using a Faro 3D laser scanner in a similar process to that carried out in Section 4.2.1. Over the course of these projects the district was converted from simple point cloud representations to BIM models to allow a semantic representation of the site. Initial energy models of each building within the district were also created by the author and members of the authors' institute.

However, a fully simulated, virtual district has been used for a number of reasons. It allows freedom with respect to scenario generation such as the type of buildings and generation technologies included. 'The Works' site contains a gas CHP, biomass boilers and gas boilers, hence, does not provide the multi-vector energy network envisaged by the author for the district optimisation case study. Furthermore, throughout this research, retrieving data from the pilot site has proven to be extremely challenging. The lack of original data with sufficient accuracy, precision and granularity meant the energy models developed for the case study could not be calibrated. Thus, any energy models produced throughout these projects are subject to the perception and best guesses of the modellers. Utilising a virtual, simulated district also has the benefit of allowing like-for-like comparison using different strategies but maintaining the same user behaviour and weather conditions. At all stages, the author has endeavoured to make the virtual eco-district as realistic as possible using a combination of detailed simulation models and environmental data from real pilot sites to model the case study district.

5.2.1 Demand-Side Design

District energy demand is modelled at a building level using the detailed building energy simulation tool, EnergyPlus [332]. In order to make the demand-side simulation as realistic as possible, Commercial Reference Building Models have been directly downloaded from the US Department of Energy's website [333]. Using these models ensures a rigorously verified, realistic model of a modern, energy efficient building without arbitrary parameters introduced based on a particular modellers perception. One of the explicit intended uses of these reference buildings is to "analyze advanced controls" [334]. It also has the added benefit of allowing this work to be open, reproducible and directly comparable to any future energy optimisation platform. Specifically, the buildings chosen to be represented in the virtual eco-district are the Large Office, Secondary School, Hospital, Large Hotel, and High-Rise Apartment. Both the hospital and hotel provide a considerable and steady baseload with the school and office generating daily peaks forming and interesting scheduling challenge for facility manager. The overall district heating consumption over a typical winter week is shown in Figure 5.2.

5.2.2 Supply-Side Design

To increase the resilience, flexibility and efficiency, and given the nature of the demand presented in Section 5.2.1, the district energy supplied from the energy centre will come from multiple sources and multiple generation units. The relatively large and consistent baseload makes a Combined Heat and Power (CHP) unit highly attractive as they achieve very high combined efficiency provided they can maintain operation for long periods. In this case, the CHP has been sized to allow it to be operational for 5000-6000 hours per annum in line with current standards [335]. By plotting the annual demand frequency, it was found that a CHP size of around 200-225kW$_{th}$ fulfilled this specification and therefore the CHP was modelled on a Power Box 138SNG with a nominal thermal and electrical capacity of 207kW$_{th}$ and 138kW$_{el}$ respectively.

In addition to the CHP providing a base load, a Heat Pump (HP) has been included to provide additional, more flexible, low-carbon, heat output. The HP has been sized relative the CHP to allow the maximum CHP electrical output to be similar to the maximum electrical input of the HP. In reality, a HP of this

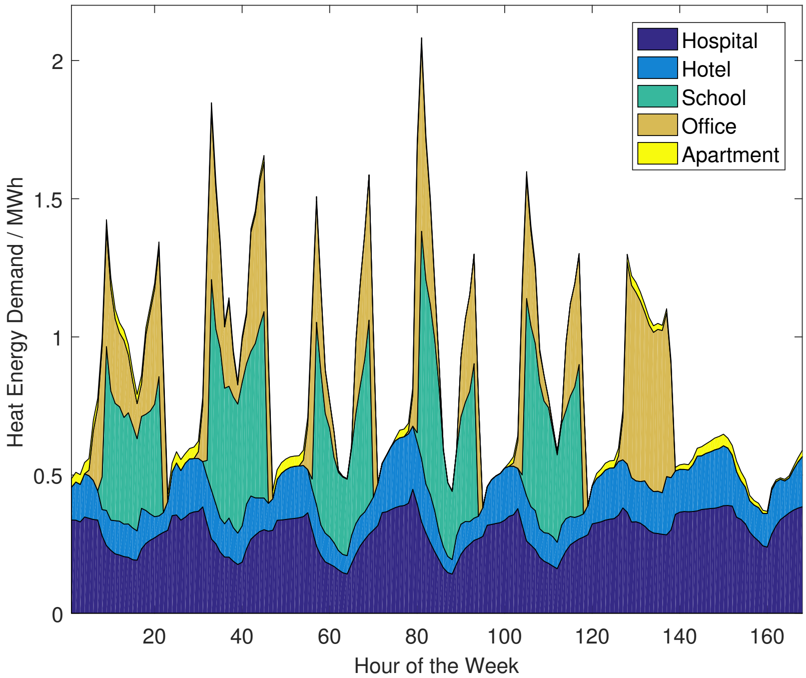


Figure 5.2: A Sample Week of Heating Demand in Winter

size is likely to be a water-source HP and due to the relatively high district heating supply temperature of 80°C the HP coefficient of performance (COP) is likely to be a relatively low 3.0 [336]. Therefore, in this case study a HP with a nominal output thermal capacity of 400kW is included meaning an electrical input of 133kW.

To provide crucial flexibility and resilience, a series of gas boilers are included to provide the peak load capacity. The total gas boiler capacity has been sized to meet the maximum possible demand of 2400kW. This has been split into four separate units of 600kW gas boilers modelled on the Rehema gas 310 eco pro 650. Whilst natural gas remains a polluting, non-renewable, fossil fuel, it is currently viewed as the least worst option during the transition to a clean, renewable future [337] and is therefore used in this case study. However, it is likely that in the near future natural gas boilers and CHP could be modified or replaced to utilise biomass, synthetic natural gas or biogas. The optimisation strategy and modelling procedure outlined in this study is equally applicable in such a scenario.

Renewable energy generation in the form of solar photovoltaic (PV) panels are included in the simulated eco-district. The modelling of solar PV generation will be based on the historical data of a real pilot site, namely ‘St Teilo’s School’ in Cardiff [338]. The modelled solar PV generation was scaled up from a building to district scale leading to a total capacity of 250kW$_{el}$. Finally, a

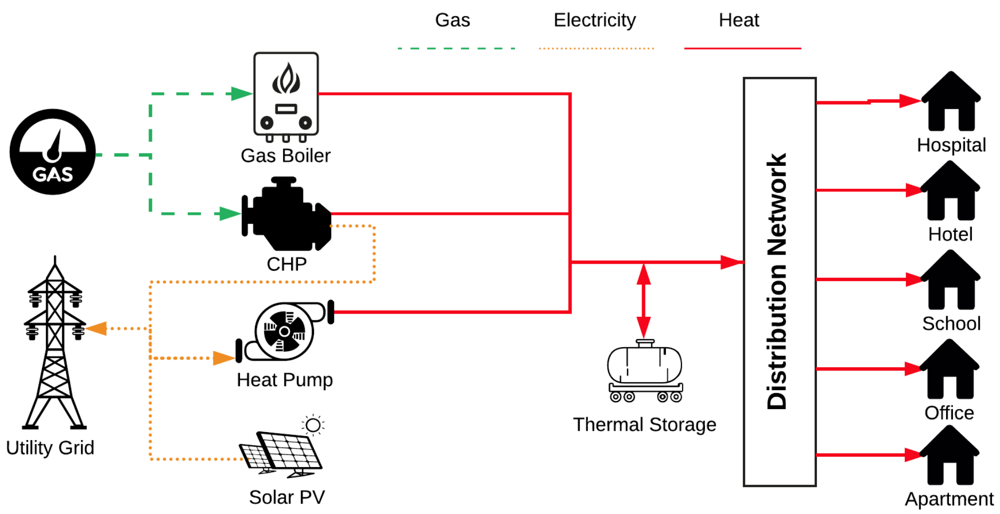


Figure 5.3: Schematic Representation of Virtual Eco-District Case Study

thermal storage tank has been included to increase the generation flexibility and providing the opportunity for an intelligent management system to capitalise on this. Note that this storage tank goes beyond the traditional buffer or mixing tanks which are commonplace in a district heating system with multiple generation sources. The thermal storage tank considered in this study is actively controlled and can be ‘charged’ by increasing the water temperature above that of the district supply temperature. A schematic representation of the virtual eco-district considered in this work is presented in Figure 5.3.

Note that in this study, the district heating network has not been explicitly modelled and it is expected that for a modern network, the heat loss during distribution will be small (around 1-2% during normal operating conditions [339]). However, it is proposed that if this control strategy was deployed in reality, the heating network characteristics such as heat losses, thermal lag and return temperatures would need to be modelled. Based on the observed district heating characteristics, the heat demand of each building relative to the energy centre would need to be adjusted. It is expected that the predicted building demand would need to be increased due to account for the distribution losses and the demand from the perspective of the energy centre would need to be brought forward to account for the propagation time.

The proposed methodology is flexible to incorporate almost any form of district heating model providing the computational time was short enough to complete within a fraction of the optimisation period. Traditional linear or gradient-based methods will always require simplified models and are hence more restricted. District heating distribution modelling will be addressed in future work and calibrated once sufficient data has been collected from pilot sites.

5.3 District Modelling

The complete district model is made up of several sub-components including controllable generation units (CHP, HP and gas boilers), a thermal storage hot water tank, uncontrollable energy generation from solar PV panels, and demand from the selected buildings. This section will outline how each of these components is modelled for use in the optimisation strategy.

5.3.1 Controllable Generation Units

The heat energy generated by the production units is simply calculated by multiplying their percentage load (an optimisation decision variable) and the nominal thermal capacity of the production unit.

$$Q_t^U = L_t^U \times C_{th}^U \tag{5.1}$$

Where Q_t^U is the heat generated by production unit U at time t due to the load percentage L and the nominal thermal capacity C_{th}^U.

The electricity produced by the CHP is calculated in a similar manner in eq. (5.2).

$$E_t^{CHP} = L_t^{CHP} \times C_{el}^{CHP} \tag{5.2}$$

Where E_t^{CHP} represents the electrical load produced at time t by a CHP with a nominal electrical capacity of C_{el}^{CHP}.

The raw fuel consumption of each generation unit is calculated based on the percentage load, nominal efficiency and part load factor. Crucially, this optimisation has the capacity to include non-linear part load functions which would need to be calculated experimentally or from data provided by manufacturers. These non-linearities are often ignored by common optimisation methods found in the literature such as MILP. In this study we have considered a polynomial regression equation relating relative efficiency and load percentage eq. (5.3) similar to that found in [340] and [341]. However, this optimisation methodology would be flexible to include a variety of part load efficiency computations such as relationships with outdoor temperature, atmospheric pressure or calculation via a black box model.

$$Rel\eta_t^U = a \cdot (L_t^U)^2 + b \cdot (L_t^U) + c \tag{5.3}$$

Where $Rel\eta_t^U$ is the relative efficiency of generation unit U at time t and a, b and c are regression coefficients.

Finally the raw fuel consumption is calculated in eq. (5.4).

$$F_t^U = \frac{Q_t^U}{\eta^U \times Rel\eta_t^U} \tag{5.4}$$

Where F_t^U is the fuel consumption (e.g. gas or electricity) of generation unit U at time t and η^U is the nominal thermal efficiency of the generation unit and $Rel\eta_t^U$ is the relative thermal efficiency due to part load characteristics. Note that in the case of a HP, the coefficient of performance (COP) will be used in the place of the nominal thermal efficiency. Due to the size of the HP simulated in this case study, it is assumed to be modular. Therefore, it is assumed that part-load factors are not applicable in the case of the HP as modules will either operate on or off, and to vary the output of the HP the number of operating modules will vary [287].

The cost of the generation, V_t is simply the multiplication of the fuel consumed at time, t, and the energy tariff at that hour, P_t, as shown in eq. (5.5)

$$V_t = F_t^U \times P_t \tag{5.5}$$

As well as cost, the district can receive income, I, through government subsidies such as the Renewable Heat Incentive (RHI) and feed-in tariff (FIT). RHI income is related to the energy provided from sources such as biomass, heat pumps and solar thermal systems. The feed-in tariff is the price at which electricity can be sold back to the national grid. They are calculated as shown in eq. (5.6) and eq. (5.7) respectively.

$$I_t^{RHI} = Q_t^U \times P_t^{RHI} \tag{5.6}$$

$$I_t^{FIT} = E_t^U \times P_t^{FIT} \tag{5.7}$$

The final objective function to be minimised, f, is the total cost of generation minus the income from RHI and the feed-in tariff calculated using eq. (5.8).

$$f = \sum_{t=1}^{24} V - \sum_{t=1}^{24} I \tag{5.8}$$

Despite not being an explicit objective of the optimisation, the CO_2 emissions resulting from each control strategy will be calculated to provide additional comparison. This was calculated using eq. (5.9), which multiplies the raw fuel consumption by their respective CO_2 emission factors, X.The emission factors have been taken from UK government statistics [342]. The electricity factor in particular would vary from country to country and year to year

Table 5.1: Summary of optimisation constants

Symbol	Parameter Description	Unit	Value
C_{th}^{CHP}	CHP Thermal Capacity	kW	207
C_{el}^{CHP}	CHP Electrical Capacity	kW	138
C_{th}^{HP}	HP Thermal Capacity	kW	400
C_{th}^{GB}	Gas Boiler Thermal Capacity	kW	2400
C_{th}^{S}	Heat Storage Thermal Capacity	kWh	500
η_{th}^{CHP}	CHP Nominal Thermal Efficiency	%	52.8
η_{el}^{CHP}	CHP Nominal Electrical Efficiency	%	35.2
η_{th}^{HP}	HP COP	-	3
η_{th}^{GB}	Gas Boiler Nominal Thermal Efficiency	%	95.75
η_{th}^{S}	Thermal Storage Charging Efficiency	%	95
P^{FIT}	PV Feed-in Tariff	p/kWh	1.82
P^{RHI}	HP RHI Tariff	p/kWh	4.17
P^{Gas}	Gas Tariff	p/kWh	1.837
X^{Gas}	Gas CO_2 Conversion Ratio	$kgCO_2/kWh$	0.18396
X^{El}	Electricity CO_2 Conversion Ratio	$kgCO_2/kWh$	0.28307

depending on the make-up of electricity generation in each specific case.

$$CO_2{}^U = F_t^U \times X^U \tag{5.9}$$

For reference a complete list of the constant parameters is included in Table 5.1. A time of use electricity tariff has been used with data retrieved from the 'Octopus Energy Agile Tariff' [343] with varying half-hourly prices linked to the wholesale electricity market. Note that a static heat pump RHI value has been given in Table 5.1. This is a necessary simplification due to the method by which this is legislated for in the UK. Heat pump RHI has two pricing tiers, receiving 9.36 p/kWh for the first 1,314 hours of the year and 2.79 p/kWh for any remaining operation. Clearly, it would not be reasonable to claim the tier 1 rate within the optimisation because it is early in the year. Instead, a weighted average value has been determined based on the number of expected hours of operation over the whole year based on the thermal demand profile.

5.3.2 Thermal Storage

A thermal hot water storage tank is modelled relatively simply in this study as a percentage of its maximum energy capacity. The maximum thermal capacity of the storage tank is assumed calculated via eq. (5.10).

$$C_{th}^S = m \cdot c_p \cdot (T_{max}^S - T^{DH}) \tag{5.10}$$

Where C_{th}^S is the maximum energy available in the storage tank, m is the mass of water, c_p is the specific heat capacity of water, T_{max}^S is the maximum temperature of the storage tank and T^{DH} is the district heating supply temperature, assumed to be a constant 80°C in this work. Therefore it is evident that the only variable in determining the 'charge' of the storage tank is the tank temperature (assuming a constant c_p).

The net heat energy taken from, or supplied to, the storage tank, Q_t^S, is determined in eq. (5.11) by computing the difference between current and previous tank storage percentage, S_t multiplied by the maximum capacity of the storage tank, C_{th}^S and the charging and discharging efficiency η^S.

$$Q_t^S = (S_t - S_{t-1}) \cdot \eta^S \cdot C_{th}^S \tag{5.11}$$

Note that modelling the thermal storage in this way assumes a uniform tank temperature and constant district heating temperature. It also lumps ambient heat losses from the storage tank with losses due to discharging and charging and is held constant in this study. However, it is likely that the ambient heat losses from the thermal storage would be related to the storage tank temperature, so eq. (5.11) could be adapted with an additional term to include this if the effect could be quantified through experimental data.

5.3.3 Uncontrollable Generation

As discussed in Section 5.2, a solar PV field of 250kW$_{\text{el}}$ capacity is considered in the described case study district. The PV generation modelling will be scaled up based on data from a real installation based in Cardiff with half-hourly recorded data over a period of two years from 2015-2016. The available length of data makes this scenario prime for the use of machine learning models to predict the next 24-hours of PV power output. Consistent with the rest of this thesis, back-propagation Artificial Neural Networks (ANN) will be trained to predict several key variables using MATLAB's 'Neural Network Toolbox'. Their effectiveness in the building and energy domain has been well demonstrated in the literature. They have been shown to achieve high accuracy, computationally efficient, and require no knowledge of the physical relationships between inputs and outputs. The theory behind ANN has already been provided in Section 3.4.1 and will not be discussed in detail in this chapter.

In the case of the solar PV model, the possible inputs were as follows; forecast outdoor dry-bulb temperature, relative humidity, solar radiation, wind speed, atmospheric pressure, the hour of the day, the day of the year, the month and the PV output at the same time on the previous day. The ANN

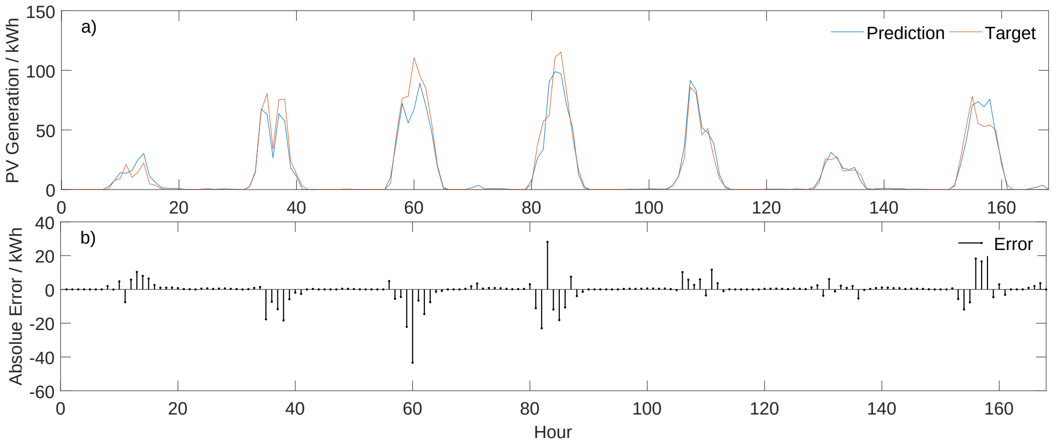


Figure 5.4: Test data comparing solar PV generation a) ANN prediction vs actual data, b) Absolute error between the two

output was hourly PV electricity generation in kWh. The complete dataset was split randomly, 70% for training, 15% for validation and 15% for testing. An identical procedure to that described in Section 4.2.4.2 was used here to find the optimal combination of inputs and ANN architecture to predict PV power output. Following the offline tuning of the ANN architecture, several inputs were found to be redundant and hence not used in the final PV ANN architecture. The resulting model uses only outdoor temperature, relative humidity, solar radiation, hour, day, month and the output 24-hours ago. It contains two hidden layers with 15 neurons in each, uses the 'tansig' transfer function and is trained using the Levenberg-Marquardt training algorithm. The training and testing R^2 values were 0.9489 and 0.9412 respectively. The prediction performance is displayed graphically for a sample week in Figure 5.4.

5.3.4 Building Demand Modelling

ANN were also used to predict the energy consumption for the next 24-hours of each building within the district. The EnergyPlus models described in Section 5.2 were run with real Cardiff weather data over two years over 2015-2016. 15% of the dataset, spread throughout all seasons, was removed to form the testing dataset. The validation dataset comprised another 15% leaving 70% of the original dataset as training data. Weather, time, date, occupancy, and previous energy consumption values were tested as inputs, and the heating energy consumption was the output. Independent ANN were created for each building to capture the particular characteristics of each energy demand profile. Once again, several possible inputs reduced the prediction performance of the ANN (e.g. wind speed) and hence were removed as ANN inputs. The resulting models used only the following variables as inputs; the hour of the day,

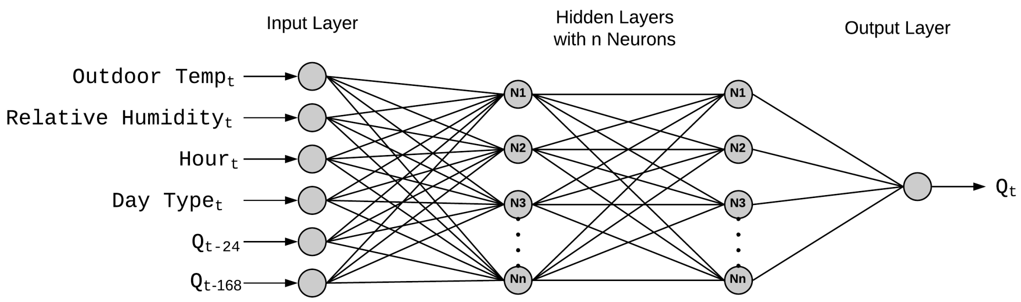


Figure 5.5: Overview of the ANN architecture for predicting building energy demand

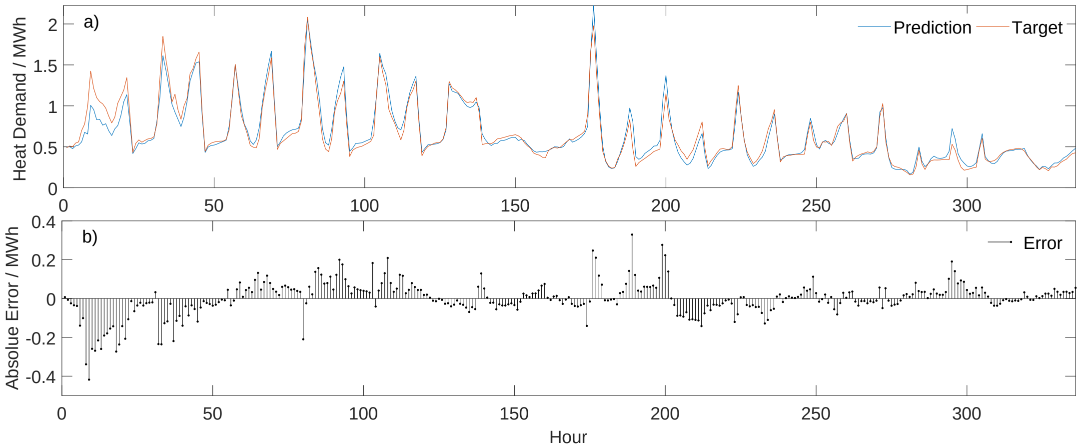


Figure 5.6: Test data comparing aggregated building demand a) ANN prediction vs target, b) Absolute error between the two

outdoor temperature, relative humidity, day of the week, energy consumption at the same timestep the previous day, and energy consumption at the same timestep the previous week. The output of each model was the hourly heating energy consumption of each building. The resulting ANN architecture is shown in Figure 5.5. For the sake of brevity and given that the aggregated total heat demand is the input to the optimisation; only a comparison between the aggregated predicted and actual demand has been shown for two test weeks in Figure 5.6. The figure demonstrates excellent agreement between prediction and target reinforced by R^2 values of 0.9745 and 0.9660 for training and testing respectively.

5.4 Supply-Side Optimisation Methodology

This section will outline the methods used to optimise the energy generation set point schedule for the proposed eco-district. The objective of the optimisation is to maximise the operational profit (note this excludes maintenance and capital costs) to the district energy hub, while meeting the thermal demands of the district. This case study will use a genetic algorithm (GA) in Model Predictive Control (MPC) format to complete this optimisation.

5.4.1 Fitness Calculation

As described in Section 3.4.2, the fitness of each individual solution within each population of the GA needs to be computed to eventually find the optimal solution. An overview of the fitness calculation procedure is shown in Algorithm 1. This procedure starts by retrieving the predicted heat demand, renewable generation, energy price tariffs and decision variables for the following 24 hours in 1 hour timesteps. The decision variables in this case are the percentage load output of the CHP and HP as well as the percentage charge of the thermal storage tank at each hour of the day giving a total of 72 decision variables. From this, the output energy of each unit is calculated as well as the primary energy input. Following this, the difference between the predicted heat demand and the heat produced from the CHP, HP and storage is calculated. Any hour in which the production does not meet the demand is automatically met by the gas boilers which provide the flexible reserve. The fitness function is modelled in this way for a number of reasons. It allows a reduction in the number of required decision variables by 24 as the gas boilers are not explicitly modelled as decision variables but implicitly controlled as their consumption will still have a significant impact on the fitness of each solution. It removes the requirement for constraint handling and penalisation of solutions which fail to meet the demand [344]. In this fitness formulation, the predicted demand is always met and this constraint cannot be breached. Note that oversupply is not explicitly punished in the fitness calculation and it is assumed that excess heat can be dumped, it is presumed that oversupply will naturally be curtailed by the optimisation as it is not economical.

Finally, the cost of primary input energy including natural gas and electricity is calculated by multiplying consumption by the relevant tariff. The income provided by the Renewable Heat Incentive (RHI) associated with the HP is calculated, along with the income received through selling excess electricity to the grid. Note that only delivered heat is eligible for RHI income, which is a government subsidy aimed at encouraging low carbon heating. Any heat that is dumped is deducted from heat eligible to gain RHI income, preventing any ‘gaming’ of the system by the optimisation. In addition, any unnecessary charging and discharging of the thermal storage incurs a reduction in the heat eligible for RHI income. This prevents the optimisation from charging the thermal storage at one hour, gaining RHI income for that hour, and then dumping the heat from the storage during the following hour. The optimisation objective

Algorithm 1: Procedure to calculate the fitness of each individual

```
Input  : L^{CHP}_{t-t+23}, L^{HP}_{t-t+23}, S_{t-t+23}, E^{PV}_{t-t+23}, Q̇^{Total}, P_{t-t+23}, S_{t-1}
Output: f
for All Individuals do
    for t = t to t+23 do
        Calculate Q_t^{CHP}, Q_t^{HP}, Q_t^S ;  // Using eqs. (5.1) and (5.11)
        if Q̇_t^{Total} - Q_t^{CHP} - Q_t^{HP} - Q_t^S > 0 then
            Set Q_t^{GB} to cover underproduction ;
        end
        Calculate F_t^{Gas} and net F_t^{El} ;   // Using eqs. (5.2) to (5.4)
        Calculate V_t and I_t ;                  // Using eqs. (5.5) to (5.7)
    end
    Calculate final fitness, f ;                 // Using eq. (5.8)
end
```

(and final fitness) is to minimise is the total cost of primary energy consumption minus the income from RHI and selling excess electricity to the grid. Note this is the same as maximising the profit received by the district operator.

5.4.2 Constraint Handling, Bounds and GA Settings

Due to the nature of the decision variables used in this study some adaptations were required to ensure all decision variables remained within bounds. Due to technical constraints, the CHP was modelled as having a lower operating bound of 70%. Therefore, the only valid values for the decision variable to take would be 0 (off) or 70% to 100%. This discontinuity could not be modelled within MATLAB's pre-existing GA functions and custom creation and mutation functions were required. During the creation function, individuals are randomly generated. For the 24 decision variables relating to the CHP, the function produces a random integer between 69 and 100 representing the load percentage of the CHP. Then any of these decision variables with a value of 69 was changed to 0. The remaining 48 decision variables relating to the HP and the thermal storage could take any value between 0 and 100.

The crossover function used is MATLAB's 'crossoverscattered' function as this recombines two parent solutions, mixing the existing decision variables and hence ensuring all solutions remain feasible with respect to the operating constraints. A custom mutation function was required for the same reason as the custom creation function. In the mutation function, each decision variable within the individual has a constant 5% probability of mutating. If the variable does mutate then it follows the same procedure outlined for the creation function. If the decision variable relates to the CHP a random integer between 69 and 100 is generated, and then, if the value is 69, it is changed to 0. These custom functions ensure that every individual remains a feasible solution throughout the optimisation procedure. Ensuring that every individual remains a feasible solution throughout the optimisation procedure mitigates the intrinsic discontinuity of the search space brought by the CHP's technical specificity and consequently makes the GA less likely to get stuck in a local optimum. The remainder of the GA parameter settings include an elite count of 5% of the population, a tournament selection function, a crossover fraction of 80%, a population size of 200, and a function tolerance of $1e-7$. Note that for all results discussed throughout this work, the GA exited each optimisation due to the function tolerance rather than the maximum number of generations or time limits, this ensured that the optimisation was well converged.

5.4.3 Real-time Control Adaptation

This optimisation will run as MPC meaning it will re-optimise every hour with updated information such as weather conditions, building demand prediction, generation unit failures etc. Operating as MPC contributes significantly towards managing the errors between predictions and reality as the most up to date information is always used. It also allows the optimisation to adapt to unforeseen circumstances and change course within a relatively short period of time.

However, despite operating as MPC, small errors between prediction and reality are to be expected and must be handled between each hourly optimisation step. To tackle this, a rule-based schedule adapter has been developed to adjust the optimal set points to meet the actual demand. Firstly, this algorithm calculates if there is an energy deficit or surplus between the net predicted heat demand and actual net demand. If there is an energy deficit, i.e. observed demand is higher than that predicted, the algorithm enacts the following steps until the deficit becomes zero:

1. Increase the supply percentage from the lead heat supplier (the CHP or HP depending on which has a higher percentage load)
2. Increase the supply from the secondary supplier
3. Increase the supply from the gas boilers

Alternatively, if there is an energy surplus, which is the case when the predicted demand is higher than the actual demand, the following steps are taken until the remaining energy surplus is zero:

1. Reduce the energy supply from the gas boiler

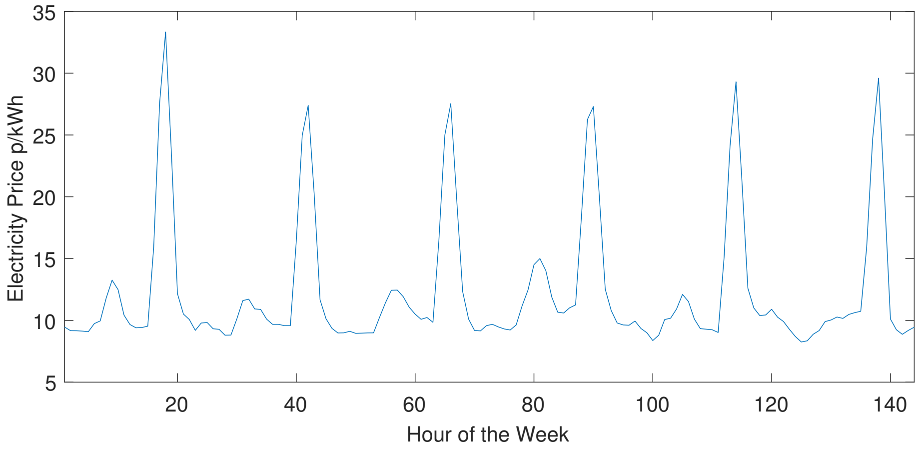


Figure 5.7: The TOU electricity tariff used for the optimisation test week taken from historical data published by Octopus Energy

2. Increase the energy stored within the thermal storage tank
3. Reduce the secondary supplier (the CHP or HP depending on which has a lower percentage load)
4. Reduce the heat production from the lead supplier

The philosophy behind this adjustment algorithm is to make limited changes to the optimal set point schedule provided by the GA. Whilst it may not achieve the absolute optimal result, it is intended as a quick, simple and heuristic method to be implemented between each optimisation timestep.

5.5 Results

The optimisation methodology described in this chapter was applied to the case study district over the simulated test week of 8th to the 13th of February 2016 using recorded weather data from the city of Cardiff. This week has been chosen as a representative winter week in the heating season. The relatively high heating demand during this week provides the best showcase for the optimisation decision making rather than a period with low heat demand in which only a small fraction of the energy centre's capacity is utilised.

To provide a comparison for the optimisation strategy a baseline, reactive, rule-based, control strategy has been developed. This strategy will not actively control the thermal storage. Instead, it will follow a priority order generation strategy. Firstly, the CHP will be used to provide the base load as it is the least flexible generator. If demand is greater than the CHP capacity then the HP will be used. If the heat load exceeds this, then the gas boilers will be utilised to meet these peak loads. The electricity pricing tariff, taken from historical

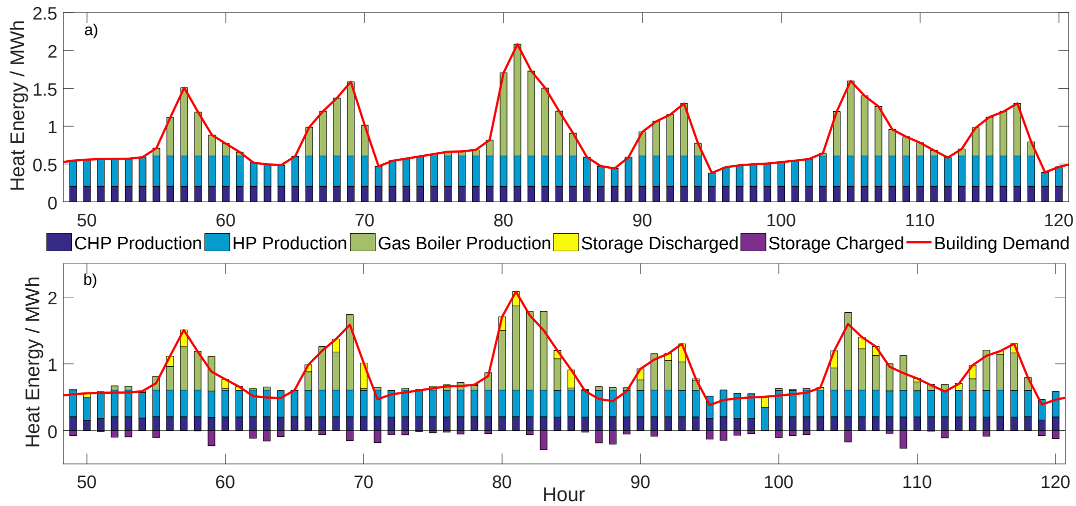


Figure 5.8: Heat generation schedule for three sample test days showing: a) Baseline Solution, b) Supply-side optimisation

prices published by Octopus Energy, over this test week is shown in Figure 5.7. The electricity price fluctuates between lows of around 9p/kWh during off-peak hours and highs of around 25-30 p/kWh during the evening peak. There is also a smaller peak in the morning, at around 8-10am.

The behaviour of the supply-side optimisation in comparison to the baseline solution is shown in Figure 5.8. For clarity, only a sample 3 days of results are shown and discussed, but the optimisation makes similar decisions on all case study days. These results demonstrate a consistent pattern, the optimisation chooses to charge the thermal storage during the early hours, during the saddle point in the middle of the day, and during the evening. The thermal storage energy is generally used to displace the gas boiler generation as this the most costly form of heat generation for the district. The result of the decisions taken by the optimisation leads to an overall reduction in CHP and gas boiler output, by 3.1% and 5.4% respectively, offset by a 6.3% increase in HP output.

These changes have a number of financial implications to the district. In the baseline scenario, the district buys no electricity from the national grid. However, in the optimised scenario, a modest total of 254 kWh is required over the week. The average price of the electricity during this scenario 9.10 p/kWh, demonstrating that the optimisation only purchased electricity during the off-peak periods when the tariff prices were lowest. The optimised scenario also sells less electricity back to the national grid, suggesting the optimisation balances the CHP electricity output and HP electricity input as it is economically advantageous to utilise electricity locally rather than sell to the national grid at relatively low prices. This point is illustrated in Figure 5.9 where generally the dips in CHP electricity output coincide with reduction in HP demand. However,

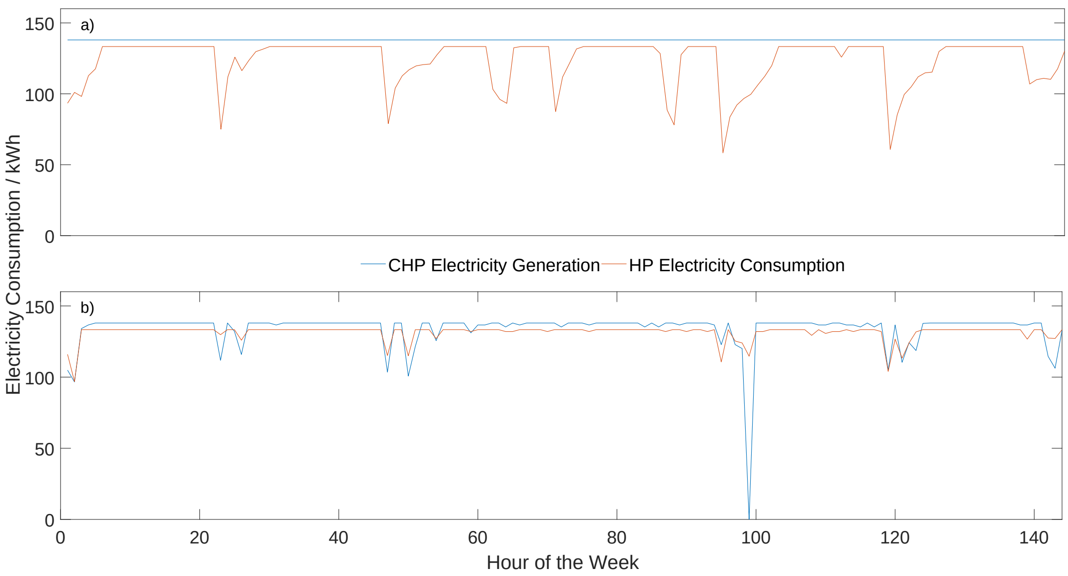


Figure 5.9: Electrical generation from the CHP and electrical consumption of the HP for: a) Baseline solution, b) Supply-side optimisation

the baseline solution maintains it's priority order strategy and over-produces electricity during low demand periods. The increased electricity costs in the optimised scenario is outweighed by a significant increase in the income from the government RHI incentive for the HP. Over the test week, the profit generated whilst fulfilling the heat demands of the district is increased from £362.25 during the baseline scenario to £524.85 by optimising the energy supply.

As well as achieving an economic benefit, the optimisation has also resulted in an environmental benefit in terms of a 3.75% reduction in CO_2 emissions. These results show that in this scenario the objective of minimising cost and reducing CO_2 emissions are mutual in this case as both objectives are achieved through reducing the gas boiler usage with thermal energy storage scheduling. The average time to complete an optimisation was 143 seconds per timestep using a 4-core, Intel i7-6700 2.60GHz, 16GB RAM PC.

5.6 Discussion

The results provided in Section 5.5 demonstrate that an optimisation based approach to controlling the energy generation of a district energy centre can provide significant gains when compared to a static control system. The optimisation methodology presented in this Chapter was able to increase the profit to the energy centre by almost 45% over the test week. As opposed to the baseline scenario, which followed a simple priority order strategy, the optimisation strategy was free to trial more experimental and unintuitive solutions. Primarily the optimisation achieved its benefits by utilising the flexibility of the thermal storage tank. The optimisation elected to charge the storage tank during the early mornings, saddle period during the middle of the day, and evenings where the demand dipped below the combined capacity of the CHP and HP. Effectively, this allowed the displacement of some gas boiler generation which is the most costly form of heat generation in this scenario.

As well as utilising the thermal storage tank, the optimisation seems to consistently choose to balance the CHP and HP load rather than favour one generation technology. This appears to be an attempt to minimise the amount of excess electricity generation provided by the CHP which would simply be sold to the national electricity grid for a relatively low price. It is unlikely that this level of finesse could be incorporated into a rule-based, reactive strategy such as that used in the baseline scenario. However, maintenance costs have been excluded from this work as it is difficult to relate decisions made on an hourly basis to the impact on maintenance cost which is more commonly estimated at an annual scale. If the increased modulation of the generation units (in particular the CHP) caused a significant increase in annual maintenance costs then some effort should be made to reflect this in the optimisation fitness function, likely through a form of penalty function.

The optimisation methodology was equipped with an error management stage based on simple heuristics to make small adjustments to the optimal solution to reflect real-time discrepancies between prediction and reality. This kind of step is essential for a methodology of this sort to be applicable to real pilot sites. The error management stage appears to have performed well in this case study evidenced by the large increase in profit and the reduction in emissions. However, it is difficult to quantify the effect of the error management stage entirely. A remaining task would be to develop a method by which this could be implemented throughout the optimised hour. Currently, the strategy receives the actual energy consumption data at the end of the hour and retrospectively amends the optimal solution for the previous hour. In reality, it would need to continually amend the solution during the optimised hour using lower-level controllers within the energy centre. This could be partially resolved by improving the timestep granularity from 1 hour to 15 or 30 minutes.

The case study results reflect the optimisation performance within the specific context of this case study district. It is not possible to extrapolate the performance of the optimisation to districts with a different energy configuration. However, in the authors' opinion, an optimisation-based approach is significantly more flexible than static rules implemented by a facility manager. Whereas it may take a human expert several months to adjust to new pricing tariffs or the addition of new equipment, the optimisation can adjust immediately if appropriately programmed. Furthermore, the optimisation is free to assess the feasibility of unintuitive solutions, for example the displayed results show an increase in electricity purchased from the grid actually led to an overall increase in profit.

This case study was based on optimising the delivery of heat energy within a district heating network, however, the principles of this optimisation methodology could easily be translated to different control variables. This could include the delivery of cooling in warmer climates via a cooling network, or the supply of electricity within a microgrid system. To demonstrate this level of flexibility, future work should aim to implement the control methodology on a wider range of scenarios with different gas and electricity prices as well as additional energy conversion technologies such as biomass, solar thermal, and power-to-gas.

5.7 Conclusion

This Chapter primarily aimed to answer research question 3:

Can taking an optimisation-based approach to the control of district heat generation improve upon existing rule-based priority order strategies?

In the authors opinion, the case study result clearly show that the developed optimisation methodology can outperform the static and reactive rules that would be implemented by a facility manager. When applied over the test week the optimisation achieved a 45% increase in profit and a 3.75% reduction in CO_2 emissions. This demonstrates that increased load flexibility within a district energy network and the adaptability this methodology provides could bring widescale advantages. This, combined with the findings of Chapter 4 will be instrumental in the remainder of this thesis.

The original contributions resulting from the chapter are a combination of the following points:

- The operational optimisation of the energy supply of a complex multi-vector energy system including natural gas, electricity, and heat.
- Utilisation of multiple ANN to predict variables such as building energy consumption, indoor temperature and PV generation.
- An intermediate, real-time control adaptation is included to adjust the optimal solution to account for prediction errors that ensures a feasible solution.
- The optimisation methodology led to a 45% increase in profit and a 3.75% reduction in CO_2 emissions.

6 | Building and District-Level Energy Management

Chapter 4 demonstrated that an adaptive, optimisation-based method for the control of building demand could be flexible to external factors such as a ToU energy tariff. Chapter 5 demonstrated that an optimisation-based approach to managing district energy supply could find the less intuitive solutions to improve upon a reactive, priority order solution. It also showed that including flexibility from a thermal storage tank helped to increase the profit generated by the district energy centre. This Chapter will effectively build upon the conclusions drawn from the initial investigations posed in Chapter 4 and Chapter 5 to provide an energy management solution that simultaneously controls both energy supply and demand at building and district-level.

6.1 Revisiting the Research Question

Specifically, this Chapter aims to answer research question 4:

Can integrated, holistic control of both energy supply and energy demand lead to greater economic and environmental benefits than independent control?

To provide an answer to this question, the virtual, simulated, eco-district set out in Chapter 5 will also be used in this Chapter. However, the complexity of the case study will be increased by including the indoor temperature set point of the office building to be directly controlled alongside the district energy generation. It is hypothesised that the flexibility provided by actively adapting the demand profile of the buildings within a district will lead to increased economic and energetic savings in comparison to just optimising at a district-level. The inclusion of building temperature control may give the optimisation some scope to shift some of the heating demand (through pre-heating) away from hours where the production of that heat generation is more expensive. The office building alone has been chosen as it is expected to have the most thermal flexibility in comparison to a hospital, hotel, school and apartment block.

On face value, this Chapter may seem small in relation to Chapters 4 and 5. This is due to the iterative nature of the research carried out in this thesis and the way it builds to the largest contribution in this Chapter. This thesis aims to continually add layers of increasing complexity, thus, it is natural that this Chapter builds on top of the content provided in previous Chapters. So while the number of pages in this Chapter is less than previous Chapters, it assumes that knowledge and information from those Chapters is brought forward to the specific case study and research question addressed in this Chapter. For example, the configuration of ANN architectures is completed in this Chapter as it is in Section 4.2.4.2, yet it no longer requires the same detailed description. In addition, the district case study is brought forward from Chapter 5 to allow comparisons to be made to an energy supply only optimisation. It is assumed in this Chapter that the reader has retained knowledge of the case study district modelling set out in Section 5.2.

The methodology described in this chapter was originally published in the journal article Reynolds et al. [330] and reformatted and expanded for this thesis.

6.2 Controllable Building Modelling

To model the controllable office building, additional modelling efforts must be made. Note that while the EnergyPlus model of the office building is identical to that used in Chapter 5, the office specific surrogate ANN models are not the same as the office energy consumption ANN developed in Section 5.3.4. In the previous Chapter, office energy consumption was simply modelled as a function of weather, day and occupancy. Instead, the office ANN model developed in this Chapter must take the decision variable (heating temperature set point) as an input.

To ensure the office remains comfortable to the occupants, it is also necessary to produce a prediction model of the average indoor temperature. Other measures of indoor comfort, such as Predicted Mean Vote (PMV) or Predicted Percentage Dissatisfied (PPD) are available, but here the volume weighted average indoor temperature has been chosen as a proxy measurement of thermal comfort as it is cheaper and more simple to measure within a building. The building-level ANN models used for the controllable office building uses the same principles as used within the building-level optimisation methodology provided in Chapter 4.

The office building model was run using weather data recorded in Cardiff in 2016. However, due to the relatively high insulation and the large amount of in-

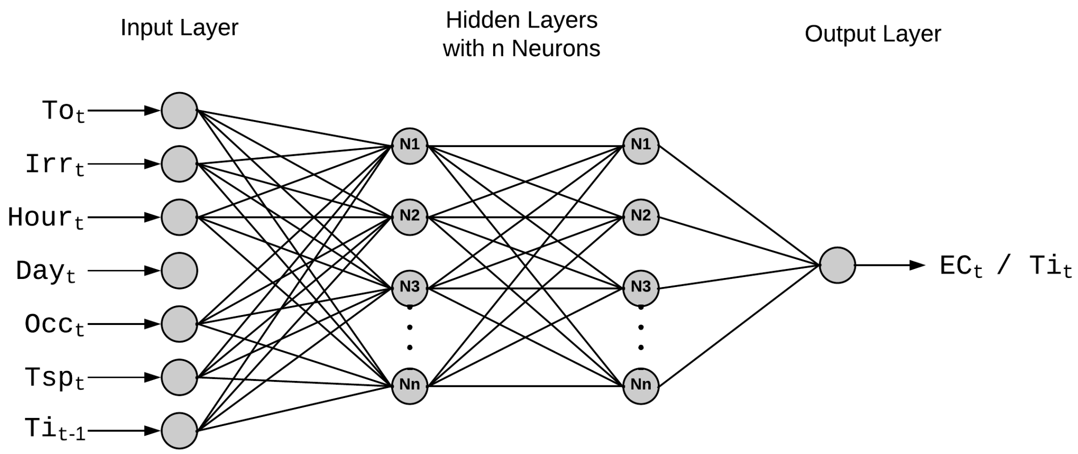


Figure 6.1: Overview of the ANN architecture for predicting office heating energy consumption or indoor temperature

ternal gains, many of the zones such as the cores, data centres and the lower-level zones are cooling dominated and do not require heating. As no heating system is simulated in these zones, they are not controlled by the optimisation and their temperatures have been excluded from the average temperature calculation.

To generate the training data, the EnergyPlus model was run ten times each with a different heating set point schedule. These set point schedules were generated by adding random numbers from a normalised distribution to the original, baseline heating set point temperature schedule. This is an alternative method of generating a range of heating set point schedules than that used in Section 4.2.4. However, this approach maintains the same core principles, namely to adequately cover the potential search space with a bias towards more sensible solutions. In addition, this method requires little manual intervention and is transferable to a wide range of building models to develop future case studies. Note that a full comparison between ANN performance resulting from the different data generation methods is not possible in this case due to the incompatible scales of the office building in this Chapter and the office building in Chapter 4. Furthermore, it is expected that the behaviour of a building of this scale will be easier to predict and model compared to a single zone within a building. A separate simulation using 2017 weather data and a different set point schedule was carried out to produce the testing data by which the ANN prediction performance could be measured.

The inputs and ANN architecture were selected using the same methods described in Section 4.2.4.2 and will not be repeated here for the sake of brevity. The resulting models receive the predicted outdoor temperature, solar irradiance, hour, day type, occupancy, the temperature set point and the indoor

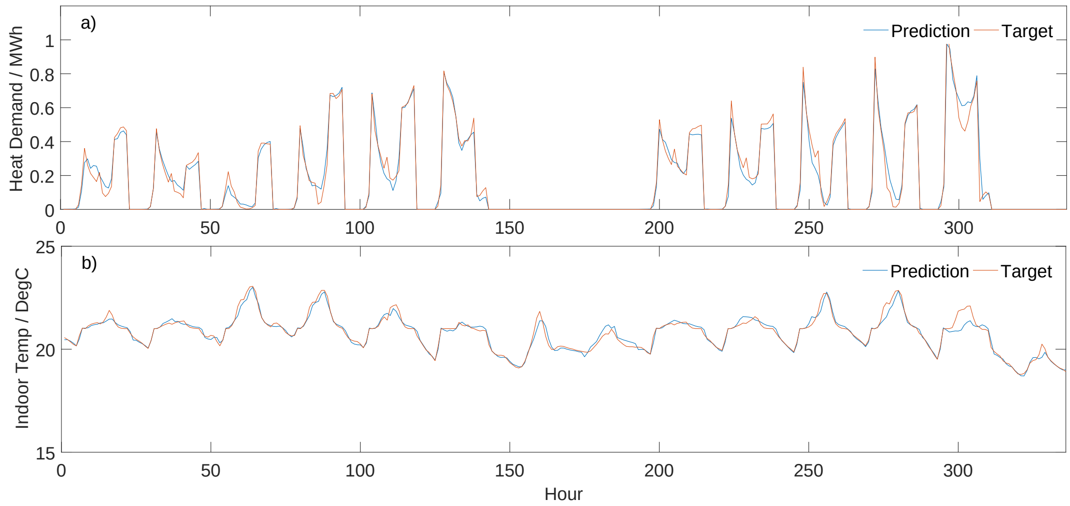


Figure 6.2: A two-week sample of ANN prediction of a) energy consumption and b) indoor temperature compared to target values

temperature at the previous hour as inputs. Each ANN has 2 hidden layers with 15 neurons in each layer, the training function is Levenberg-Marquardt and the transfer function between each layer is the 'tansig' function, this is illustrated in Figure 6.1.

One ANN outputs the predicted hourly energy consumption, the other predicts the hourly average indoor temperature. All of these variables, except the previous hour indoor temperature, are retrieved for the next 24 hours. In the case of the previous indoor temperature input, the first value can be retrieved from the building BMS system. The first hour inputs are passed to the ANN which predicts the indoor temperature at time t. This predicted value of indoor temperature is then used as the input to predict the indoor temperature at time $t + 1$ and so on until the complete 24-hour profile has been predicted. This full range of inputs is then used to predict the 24-hour profile of the energy consumption.

The ANN developed using this method and implemented through the rest of this chapter have a high accuracy to predict office energy consumption and average indoor temperature. For energy consumption, an R^2 value of 0.9712 and 0.9561 is achieved for training and testing data respectively. For temperature prediction, an R^2 of 0.9805 and 0.9679 has been achieved for training and testing data respectively. The relatively modest fall between training and testing shows no obvious signs of overfitting. A two-week sample of the ANN prediction compared to the target values is shown in Figure 6.2. This figure demonstrates the ANN has effectively learned the trends within the training data and can effectively model the building characteristics.

Algorithm 2: Procedure to integrate building and district-level optimisation

Input : Weather, t, Day, Tariffs, S_{t-1}, T^i_{t-1}
Output: L^{CHP}_t, L^{HP}_t, L^{GB}_t, T^{sp}_t
for *t = t to* t_{end} **do**
  for *t = t to t+23* **do**
    Predict: $\dot{Q}^{Hosp}_t$, $\dot{Q}^{Sch}_t$, $\dot{Q}^{Apar}_t$, $\dot{Q}^{Hot}_t$, E^{PV}_t ; `// Using ANN Models in Section 5.3.4`
  end
  Run GA;
  while *GA state = Running* **do**
    for *All Individuals* **do**
      Predict: $\dot{Q}^{Office}_t$ and T^i_t ; `// Using ANN Models in Section 6.2`
      Sum predicted demand Q^{Total} ;
      Calculate Fitness, f; `// Using Algorithm 1`
    end
  end
  Input T^{sp}_t to BCVTB to calculate actual $\dot{Q}^{Office}_t$ & T^i_t ;
  if *Predicted* $\dot{Q}^{Total} \neq$ *Actual* $\dot{Q}^{Total}$ **then**
    Run Error Manager Algorithm ; `// As Described in Section 5.4.3`
  end
  $t = t + 1$
end

6.3 Optimisation Methodology

To include building-level demand control alongside district-level supply optimisation a number of adaptations need to be made to the GA procedure outlined in Chapter 5. The complete optimisation procedure is shown in Algorithm 2. The decision variable matrix now contains 96 values, 24 relating to the percentage load of the CHP, HP and the thermal storage, as well as 24 related to the heating set point temperature of the office (i.e. the same decision variables as Chapter 5 plus decision variables relating to the office set point temperature). The procedure requires an additional step compared to the supply side optimisation. Firstly, the additional variables such as the forecast weather conditions, time, date, occupancy and energy tariffs are retrieved. Then the day-long, hourly load predictions of the solar panels and the heat demand of the four non-directly controlled buildings are made using the various ANN described in Section 5.3.4. The static GA control parameters are provided, and the GA is initialised.

6.3.1 Fitness Function

Within the fitness function, the initial stage retrieves the individual's heating set point schedule, T^{sp}, and from this determines the 24-hour indoor temperature, T^{i}, and energy consumption profile Q^{Office}. To ensure occupant comfort is met, any solution which leads to an hour where the indoor temperature is below 19.5°C or above 24°C is discouraged. This is done through penalising the individual by overriding that hour's energy consumption to 10,000 kWh. This penalty is very harsh and is intended to ensure that all solutions that breach the comfort bounds are discarded through the GA process. Note that the comfort bounds of 19.5°C and 24°C could be altered depending on user preference and the specific building in question. Once the adjusted energy consumption profile has been calculated it is added to the predicted demand of the other four buildings and the remainder of the fitness function is identical to that explained in Section 5.4.1 and shown in Algorithm 1.

6.3.2 Constraint Handling, Bounds, and GA Settings

When optimising both building demand and district supply, the GA parameter settings have remained the same as that described in Section 5.4. The creation and mutation of the CHP, HP and thermal storage variables is also identical. The set point temperature upper bound is held constant at 24°C whereas the lower bound is 19.5°C for the occupied hours (between 6 am and 10 pm) and 12°C during the hours outside this.

To speed up the optimisation, an additional measure has been taken. During the MPC process, a 24-h schedule of heating set point temperatures and generation load percentages is generated, yet only the first hour values are used. Rather than discarding the remaining 23 hours worth of set points, they are inserted as an individual in the initial population of the subsequent hours optimisation (the first hour values are dropped, all solutions translated by one hour, and the final value for each unit / set point is a duplicate of the 23rd hour to ensure correct matrix length). This provides the optimisation with a strong initial candidate to aid the convergence of the GA once the first hour has been complete. Note that the GA procedure continues in the same way, with full freedom to develop new solutions and ignore that initial solution if it performs poorly for the new situation. The benefits of this optimisation 'bootstrapping' is demonstrated by comparing Figures 6.3 and 6.4. When the optimisation was run with an entirely random initial population, Figure 6.3, the optimisation took just over 1000 generations to converge to the function tolerance. However, when the optimal solution from the previous timestep is placed in the initial

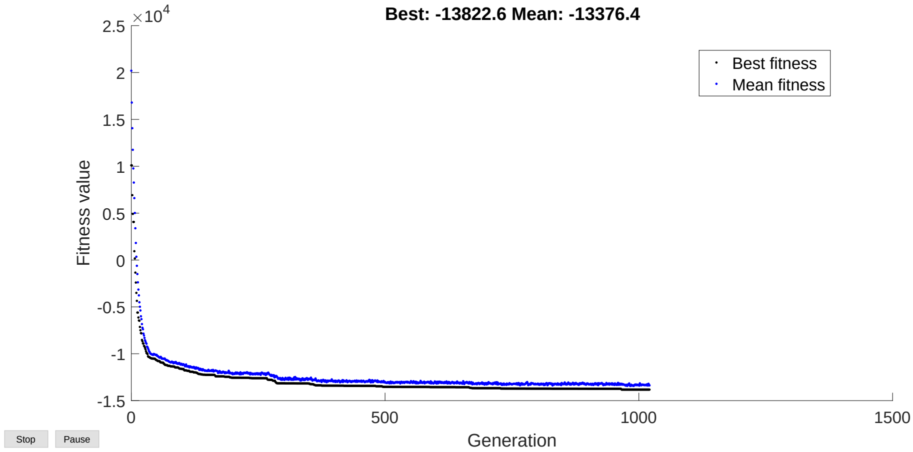


Figure 6.3: The GA convergence to an optimal solution with random initialisation

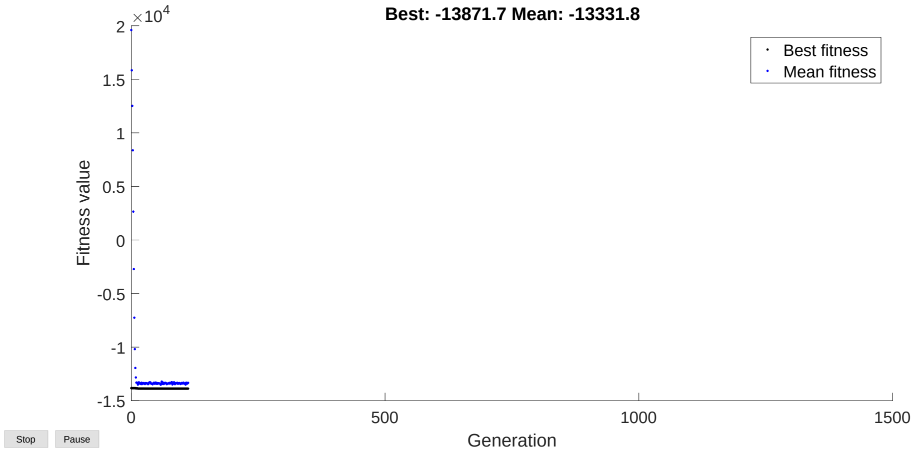


Figure 6.4: The GA convergence to an optimal solution with the previous optimal schedule included in the initial population

population, Figure 6.4, the optimisation only required around 100 generations and the final optimal solution is very close to the initial solution.

6.3.3 Real-Time Control Adaptations

To demonstrate how the optimisation procedure would operate in real-time, this study is using the Building Controls Virtual Test Bed (BCVTB) [345]. Similar to its use in Chapter 4, BCVTB allows the coupling between the simulation software, EnergyPlus, and external optimisation algorithm based in MATLAB. An illustrattion of the BCVTB set up in this case study is provided in Figure 6.5. Each timestep of the optimisation is simulated to run on the hour, every hour of the day. The optimisation is expected to complete within 10 minutes. Once the optimisation is complete, the optimal set point temperature at that timestep is passed, via BCVTB, to be implemented in the EnergyPlus simulation model of the office building. The simulation model is run for the remainder of that

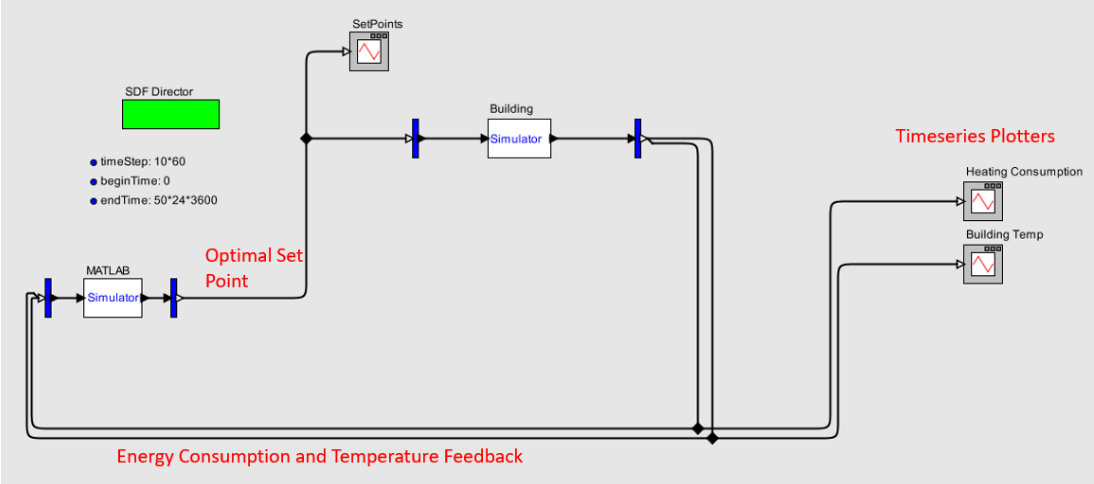


Figure 6.5: The connection of the office EnergyPlus model with the MATLAB optimisation via BCVTB

hour with the optimal set point temperature until the next optimisation starts at the beginning of the next hour. During this time, the EnergyPlus simulation model has been recording the weighted average indoor temperature of the office building. The hourly average temperature is passed to MATLAB to be utilised in the next optimisation timestep. As well as the average indoor temperature, the sum of the energy consumption over that hour is also sent to MATLAB and combined with the actual energy consumption of the other four buildings. This information is used by the same error management algorithm described in Section 5.4.3. BCVTB is used to recreate as close to real-world conditions as possible, but if deployed on a real case study it would not be required. Instead, an intermediary connection between the optimisation and the BMS would be used as the BMS has the actuation and measurement capabilities required by the proposed optimisation strategy. The complete optimisation strategy including the management of energy supply and energy demand via the controllable office building is illustrated in Figure 6.6.

6.4 Results

The combined, supply and demand optimisation strategy described in this chapter was run for the same test week as that described in Chapter 5. The results of this optimisation will be compared against both the supply only optimisation and the baseline scenario. To understand the solution generated by this optimisation strategy, the energy consumption and indoor temperature of the controlled office building is compared with the baseline heating strategy in Figure 6.7. The baseline heating set point schedule uses the same schedule every day, maintaining a temperature of 21°C during occupied hours. The re-

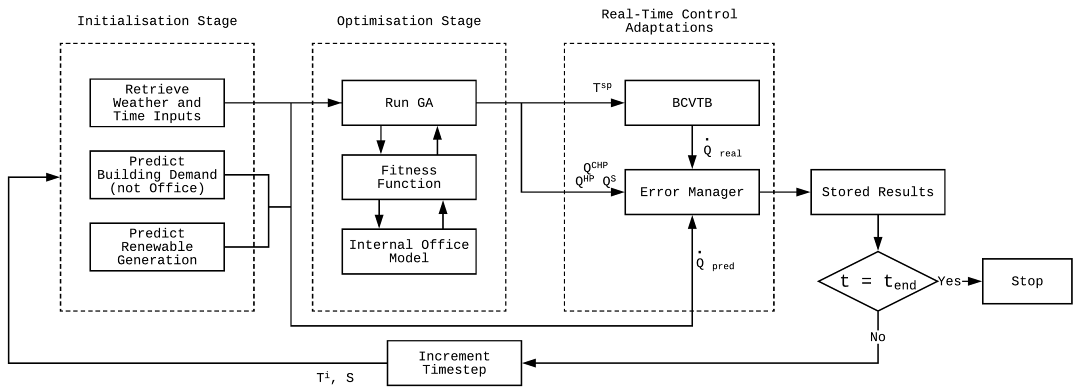


Figure 6.6: Flowchart outlining the complete optimisation procedure incorporating control of energy supply, energy demand and error management

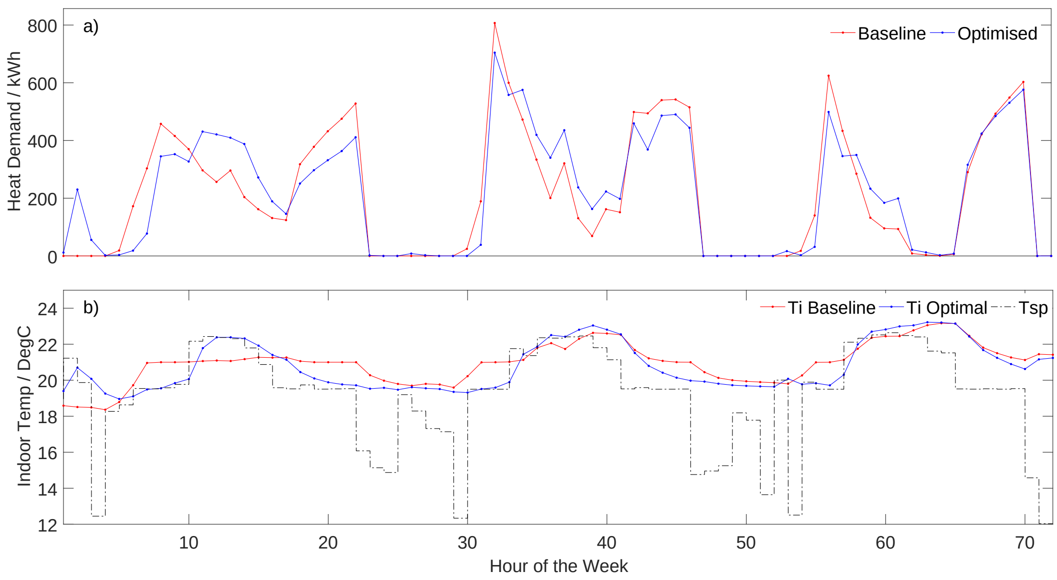


Figure 6.7: Baseline vs optimised results for the office building for three sample test days showing: a) Energy consumption, b) Indoor temperature

sults demonstrate an attempt to pre-heat in the early hours of the morning to reduce the morning peak load. It maintains a lower setpoint temperature between 7 and 10 am and then raises the temperature during the midday period where district demand is lower. This is a cheaper time for the district to provide heat and also reduces the afternoon energy peak.

Despite consuming similar amounts of energy during the displayed day, the inclusion of the demand-side control has provided additional flexibility to the optimisation. The optimisation decisions for the energy generation are shown over three days in Figure 6.8. The decisions made on the generation side are very similar to those made during the supply-only optimisation but with a slightly modified demand profile. The thermal storage is mainly charged during the morning, evening and midday saddle period and discharged during peak

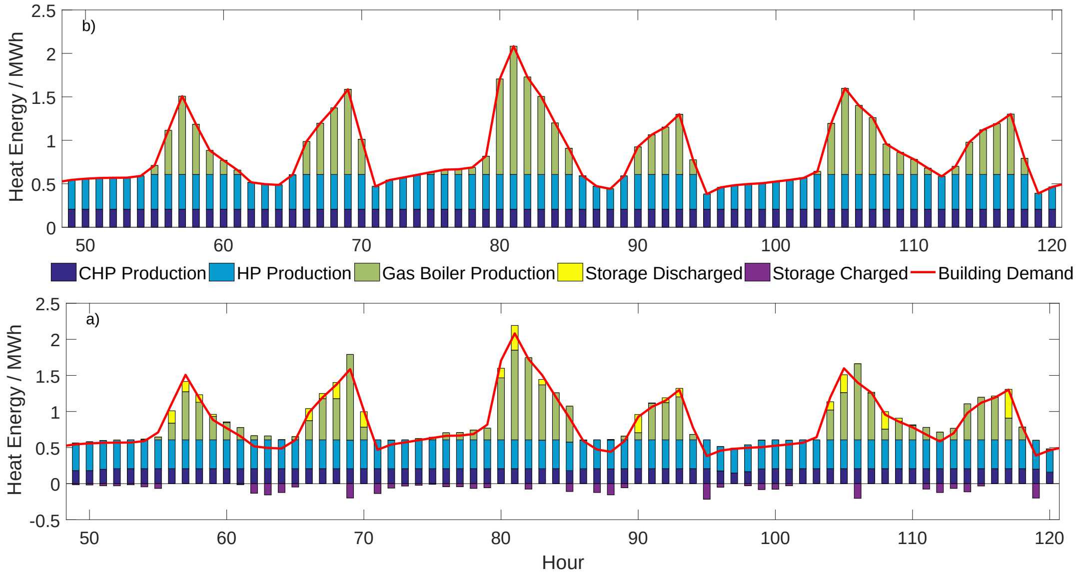


Figure 6.8: Heat generation schedule for three sample test days showing: a) Baseline solution, b) Combined supply and demand optimisation

periods to displace some gas boiler generation. Once again, the optimisation aims to balance the electricity input of the heat pump with the electricity output of the CHP rather than simply favour a lead heat producer as is the case with the baseline solution as shown in Figure 6.9.

A detailed breakdown of the three scenarios is given in Table 6.1. The statistics contained in this table show the average load from the three generation technologies over the course of the week. In addition it shows the total costs of buying electricity and gas over the test week and the income received from selling electricity to the grid and the RHI from the heat pump. Evident from the results in the table, both the supply only and supply and demand optimisations reduce the amount of electricity sold to the grid and increase the amount of electricity bought with respect to the baseline scenario. This is reflected in the lower average CHP loads but offset by an increased heat pump load. The use of the thermal storage allows a reduction in the reliance on the gas boilers hence a reduction in total gas cost. The increase in heat pump RHI income and the reduction in gas cost more than offsets the loss of income from selling electricity to the grid at relatively low prices. The differences between the supply only and the supply and demand optimisation is a further decrease in gas boiler usage, reduced electricity costs and greater electricity income. This is achieved through the intelligent load shifting of the office building heating consumption and the additional flexibility provided by directly controlling the office.

A macro-level comparison of the overall net profit and the CO_2 emissions

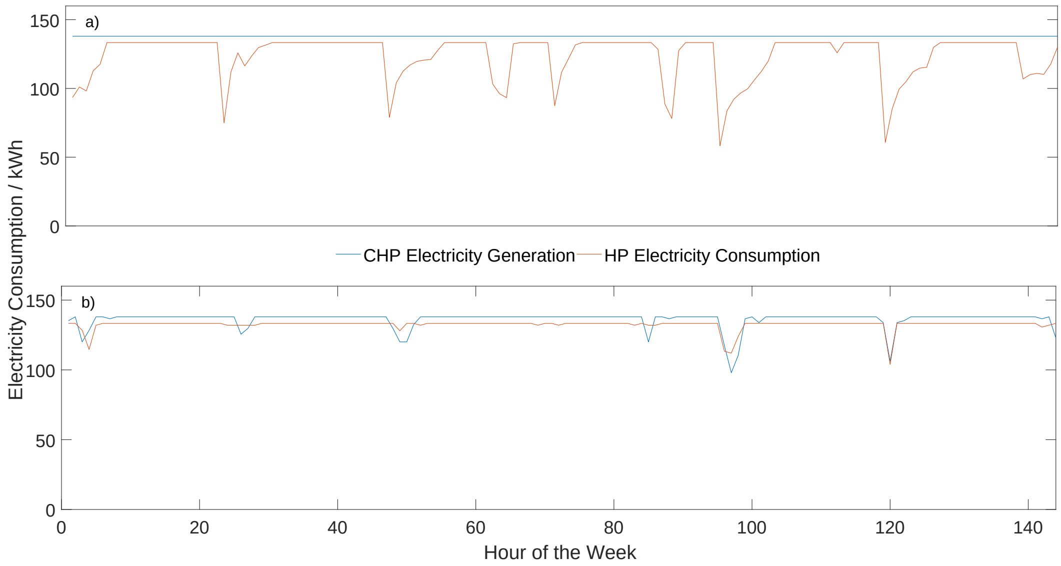


Figure 6.9: Electrical generation from the CHP and electrical consumption of the HP for: a) Baseline solution, b) Combined supply and demand optimisation

Table 6.1: Detailed breakdown of scenario results for the test week

Scenario	Average Load / kW			Electricity Income / £	Electricity Cost / £	Gas Cost / £	RHI Income / £
	CHP	HP	GB				
Baseline	207.00	371.01	299.58	75.38	0	1940.96	2227.83
Supply Only	200.56	394.22	283.52	8.42	22.87	1861.12	2361.12
Supply and Demand	204.14	397.31	278.09	48.87	7.54	1861.13	2375.03

associated with each scenario is shown in Table 6.2. Over the course of the entire week, the additional flexibility provided by controlling the combined supply and demand optimisation achieves a 52.92% increase in profit compared to the baseline control strategy which is 8% higher than optimising just the energy supply. As well as an increase in profit compared to the baseline and the supply only optimisation, this strategy also results in the lowest CO_2 emissions of the three scenarios. Once again the reduction in CO_2 emissions is largely as a result of reduced gas boiler consumption. The average time to complete an optimisation was 145 seconds per timestep using a 4-core, Intel i7-6700 2.60GHz, 16GB RAM PC which is well below the foreseen 10 minute limit.

6.5 Discussion

In addition to the points discussed in Section 5.6, which remain valid here, this Chapter has generated additional points of interest. Primarily, the outcomes shown in Section 6.4 demonstrate that including building level, demand-side

Table 6.2: Summary of results for the test week

Scenario	Profit (£)	Change in Profit (%)	CO_2 Production (kg)	Change in CO_2 (%)
Baseline	362.25	-	19437.05	-
Supply Only	524.85	44.88	18708.67	-3.75
Supply and Demand	553.96	52.92	18660.55	-3.99

flexibility at a district level, energy supply optimisation problem can lead to increased benefits to the district both financially and environmentally. The combined supply and demand optimisation outperforms the supply only optimisation by an additional 8% despite only being able to control a proportion of one out of five buildings in the district. In this scenario, the building not only shifts load based around energy prices but directly impacts the cost of energy for the entire district network. In theory, the savings achieved through the building load shifting could not only be passed on to the office building but could also provide savings for all consumers within the network.

The methodology presented in this Chapter has aimed to predict the key variables such as building demand and PV generation without assuming known loads beforehand at 100% accuracy. This is a required vital step for a strategy such as this to be implemented in reality. However, the input weather forecasts have been assumed to be completely accurate and known in advance. This was due to a lack of historical record of weather forecasts alongside the actual measured weather data that was available. The accuracy of short-term weather predictions is generally very high and accessible from modern weather services companies, therefore, an assessment of how weather forecasting errors effect ANN prediction was considered beyond the scope of this study but the impact should be assessed in future studies.

In addition to incorporating weather forecasts, this methodology should also endeavour to include an accurate district heating model in the future. It was not possible in this work due to a lack of original data to be able to characterise the heat loses within the distribution network and the time lags from heat production at the energy centre and delivery to the buildings. In the authors opinion, this should not significantly impact the performance of the proposed optimisation methodology as it will just modify the demand profile. As long as the demand profile is modelled accurately the optimisation will be able to find a reasonable solution. Nevertheless, the distribution network will have an impact on the demand profile with respect to the energy centre so would be required for real-time deployment.

The case study district optimised in this study is a centralised district where it is assumed the heat energy required by each building is produced and distributed from a central energy centre where the buildings have no alternate means of producing energy. It also assumes the controller of the energy centre would have direct control over the buildings within the district which may be the case for a single owner business park, university or municipal centre. This has led to a centralised optimisation approach that is not necessarily adaptable to districts with different ownership structures and also poses issues of scalability if there are additional controllable generation sources or more directly controllable buildings. Therefore, future work should aim to develop and compare the performance of a more decentralised optimisation framework where local building-level optimisation would interact iteratively with a district level supply optimisation.

This work poses serious questions on the suitability of our energy markets. The implementation of this kind of energy management solution requires significant modernisation of existing regulation and for the consumer to play an increasingly active role. Previously, the consumer has been viewed as a constraint on the energy networks with a simple relationship with the energy supplier. The consumer simply requests energy, it is provided by the supplier and the consumer is billed for the energy they use. This model requires an overhaul in an environment where energy generation is becoming increasingly decentralised and managed locally. The relationship must become bi-directional in that energy will be traded both to and from the energy grid to the end user. Not only will prosumers have the capability to sell energy back to the grid, they could also provide ancillary services to the grid in terms of load balancing through use of local energy storage devices.

If the energy grid follows the vision of the smart grid, which will consist of many interconnected microgrids, there is potential that collectives of small consumers could participate in demand response events represented by a microgrid-level agent or aggregator. To achieve this, a microgrid (or district-level) optimisation, similar to that discussed in this Chapter, would have a vital role to play in ensuring end users could simultaneously reap financial benefits whilst providing a service to the energy networks.

The example provided in Figure 6.10 demonstrates a multi-use, multi-vector, district energy system with various energy generation technologies and multiple owners. In the smart grid vision this district could be viewed as one node within the wider national grid with an aggregated, net energy exchange. The district could consist of multiple energy conversion and generation technologies including the more traditional, fossil fuel generators, alongside renewable technologies and power to gas. As well as multiple conversion technologies, energy could be generated and stored at both building and district-level. A

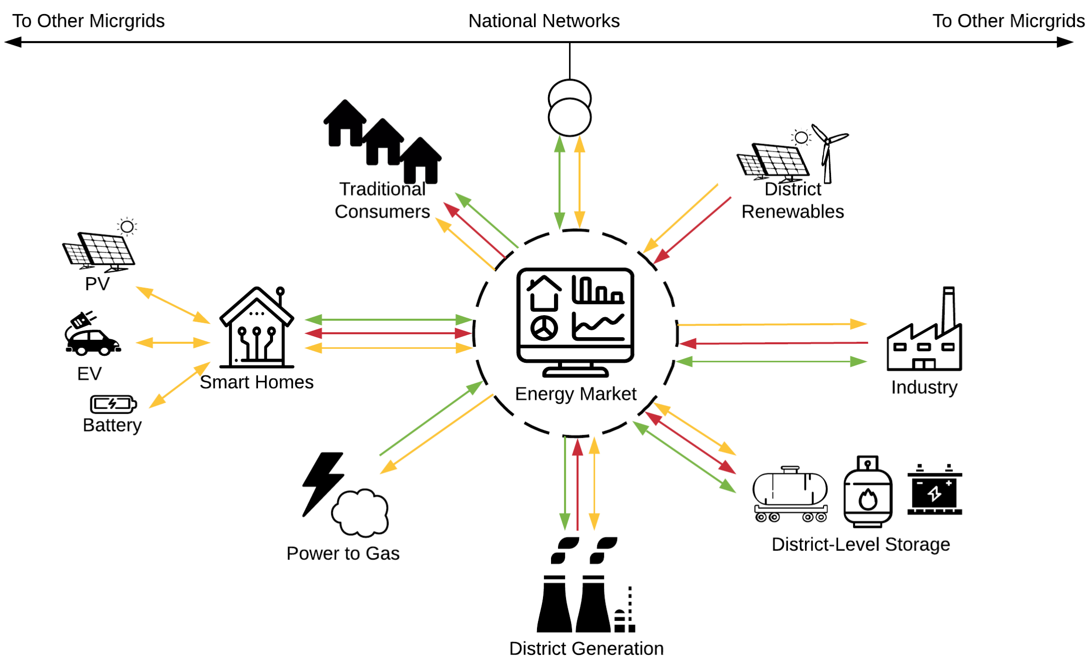


Figure 6.10: Possible interactions within a hypothesised future energy market for a multi-vector district, lines refer to: Yellow - Electricity, Red - Heat, Green - Gas

market-based energy controller would sit in the centre of this dynamic, multi-vector, district energy system. This actor would be responsible for trying to match energy supply with energy demand within the district. Due to the multiple stakeholders involved, it is likely that this service would have to be coordinated by a 3rd party ESCo (Energy Service Company) by means of bidding and resolving fair prices. In the background, the central coordinator would also be connected to the national scale networks and have access to their energy tariffs and demand response requests which it could pass on to consumers.

For this vision of a future energy market to become reality, a significant educational push will be required for consumers. Consumers have become comfortable with using energy at any period of the day for the same price. Many consumers may feel aggrieved if energy prices become higher during their higher consumption periods and they may feel as though they are unable to shift their energy consumption due to working patterns. To overcome this, end-users need to become incentivised to purchase components such as home battery systems. The benefits of these systems need to be translated into clear financial gain to the consumer. With technology such as home battery systems, vehicle-to-grid electric vehicles, and renewable energy systems, the consumer will largely be free to consume energy as they normally would, yet still achieve cost savings in a new energy environment. Of course, one cannot expect the individual to be managing these devices manually, it is unreasonable to expect the average consumer to wake up and charge all of their devices in the early hours because that is when prices are cheapest. An intelligent, automated agent, should manage these devices on behalf of the end user. The consumers preferences should be input through comfort constraints rather than in terms of energy. For example, this could be setting temperature bounds through the day or a minimum electric vehicle battery range in the morning. It would be the role of the intelligent agent to work around these constraints whilst analysing the district energy market to save the consumer money. The work carried out in this thesis goes some way to illustrating what these controllers could achieve when managing the thermal aspect of a building.

An additional consumer concern could be raised around security and privacy. Within the district energy market, minimal information should be exchanged between individual consumers and the central coordinator. Within the home, many consumers are growing accustomed to digital assistants offered by large companies such as Google, Amazon and Apple. Therefore, it is expected that consumer attitudes should remain relaxed towards smart energy management controllers. However, security improvements remain imperative within the IoT sector generally. These are arguably more critical when it comes to the security of energy supply in comparison to the security of entertainment devices. The emergence and development of blockchain technology could provide a secure, transparent and indisputable method to facilitate energy exchange and foster trust in consumers. All energy exchanges from peer-to-peer and for consumer to the central coordinator would be indisputably logged within a distributed ledger. Blockchain could override the requirement for several intermediary companies to facilitate such financial and energy-based transactions and reduce the barrier to entry for typical consumers within such a marketplace.

6.6 Conclusion

This Chapter primarily aimed to answer research question 4:

Can integrated, holistic control of both energy supply and energy demand lead to greater economic and environmental benefits than independent control?

This question has been addressed by comparing the optimisation carried out in Chapter 5, which only optimised the energy supply, with an adapted optimisation methodology that optimised building demand alongside energy supply. Whilst the case study presented in this Chapter only controlled the heating set point temperature of a single building within the district, it achieved an additional 8% increase in profit for the energy centre compared to optimising supply alone. In total, the combined supply and demand optimisation achieved a 52.92% increase in profit compared to the baseline solution and also led to the lowest CO_2 emissions of all scenarios.

The original contributions resulting from the chapter are a combination of the following points:

- A simultaneous optimisation of energy supply and demand through controlling a building heating set point temperature in conjunction with district heat generation.
- A direct comparison with a baseline solution and supply only optimisation demonstrates the value in utilising building thermal flexibility.
- This also encompasses the contributions from Chapter 5, namely the optimisation of a multi-vector energy system, the prediction of key variables and the real-time control adaptations.
- Simultaneously controlling energy supply and demand a 53% increase in profit to the energy centre compared to the baseline scenario.

7 | Semantics: Interoperability and Scalability

Chapters 4 to 6 have developed novel energy management solutions and applied them to bespoke case studies to demonstrate their effectiveness. This Chapter will aim to explore the ways in which the energy management strategies could be deployed on a wider scale using a more standardised approach. Furthermore, this Chapter will aim to provide the vision of how the work carried out in this thesis relates to wider trends and challenges within the field. By demonstrating additional research trends, this Chapter will show the relevance of this research and how these techniques can converge to produce a new generation of building and district energy management controllers.

7.1 Revisiting the Research Question

This Chapter specifically aims to address research question 5; restated here as:

Can a semantic web approach ease the deployment of advanced energy management strategies on a wider scale and aid integration with additional domains?

This Chapter will address the above research question in a different way compared to Chapters 4 to 6. This research question requires an analysis of wider research trends to provide a forward looking, discussion-based approach rather than the case study approach of the preceding Chapters. This Chapter will make the case for the use of semantic web innovations as the foundation to provide a robust basis from which the energy management strategies developed in this thesis could be deployed.

7.2 The Role of Semantics

The title of this PhD thesis is *"Real-Time and Semantic Energy Management Across Buildings in a District Configuration"*. The semantic aspect of this work derives from the contextual nature of the optimisation methodologies developed in Chapters 4-6. These methodologies extract meaning from wider metadata including weather forecasts, occupancy, renewable energy generation and energy demand. All of the relevant data is linked to provide a more holistic energy management approach, exploring the context of the specific situation. However, in this thesis, the labelling and linking of data is achieved in an ad-hoc fashion without the use of formalised ontologies and semantics. This decision was made in light of two recent PhD studies completed within the author's institute that developed upper-level ontologies within the smart water, building and energy domains [164, 346]. Both of these PhD projects hypothesised that their developed ontologies could aid the intelligent management of smart building and city infrastructure. Therefore, throughout this thesis, replication of similar ontologies was deemed beyond the scope of this thesis and unnecessary. Instead, this thesis is focussed on demonstrating the benefits of increased, contextualised data in energy management.

Nevertheless, having been involved with several research projects that aim to utilise and exploit semantic web technologies, the scope and application of semantics to the built environment can be detailed here, including how they relate to the energy management strategies developed in this thesis. This section will present samples of objects and concepts in an ontological fashion at building and district-levels to demonstrate how the energy management data sources could be semantically linked and retrieved from central models. Whilst the use of ontologies was deemed unnecessary in the initial proof of concept energy management strategies laid out in this thesis; it argues that for scalability and replicability to additional pilot sites, formalised ontologies should be utilised.

To demonstrate the potential for semantic linking at a building-level, Figure 7.1 has been provided. This figure aims to provide just a small sample of the concepts and objects that are modelled via BIM or building energy models and how they interconnect, it is not intended to be exhaustive. Concepts encapsulated by ovals are utilised within the optimisation case study developed in Chapter 4. Note that most of these concepts are already captured in existing energy models and / or in the BMS. Many of the physical properties of a building are duplicated in both the BIM and energy model although they may not use the same naming conventions. Note that this is not an ontology created by the author, it is simply a hypothesised data structure provided to illustrate the kind of data integration envisaged by the author to achieve a semantic vision. Similar mapping of energy, control and physical building properties has already been conducted through the KnoHolEM project [174]. It is postulated

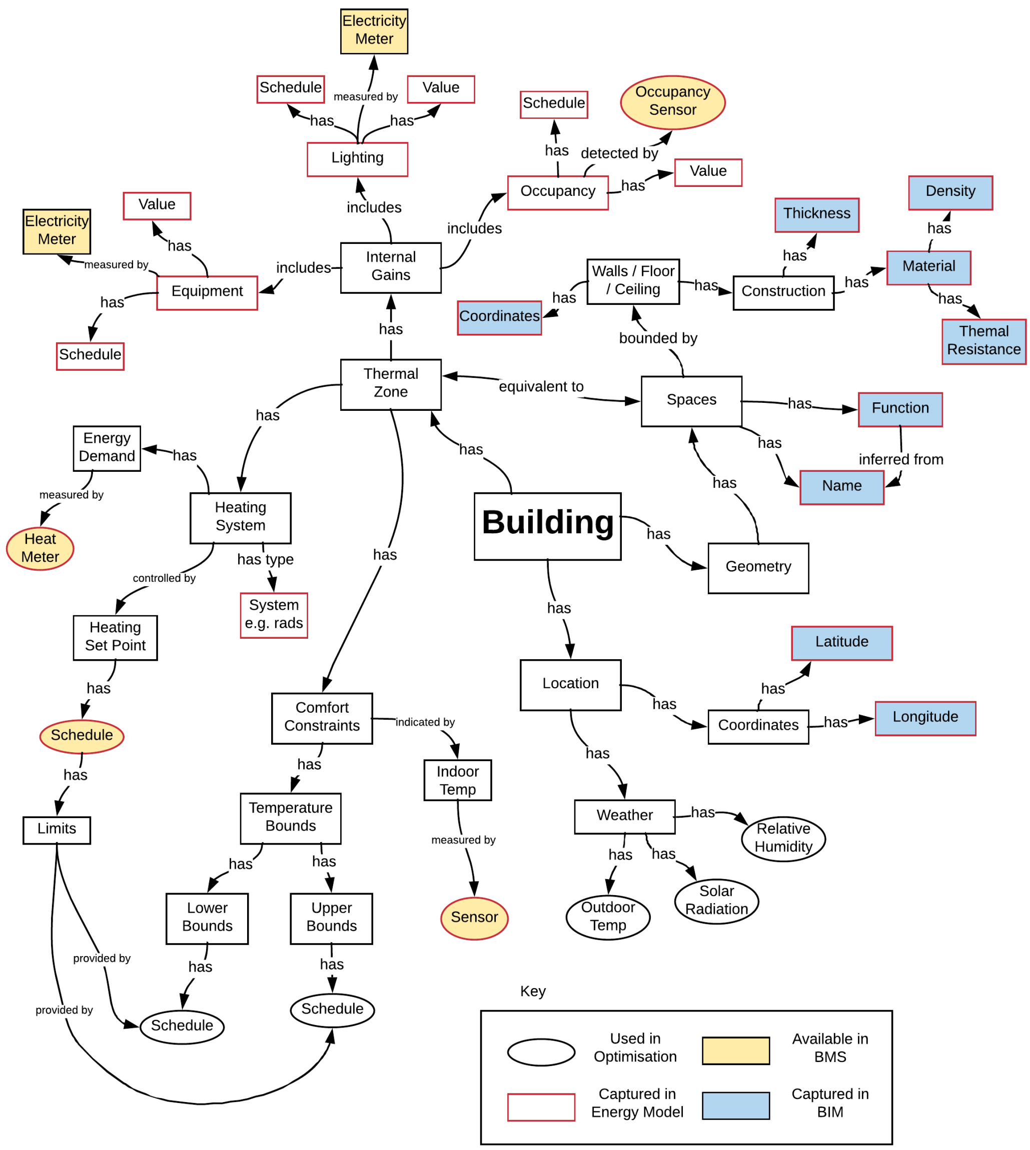


Figure 7.1: An illustration of building-level objects and concepts, the relationships between them, and where they can be retrieved from

that the KnoHolEM ontology (or other similar work) could be used to deploy the building-level optimisation developed in this thesis with little requirement for extension.

A similar district-level data structure is presented in Figure 7.2. This image takes a sample of the concepts included in the data structure used in the PENTAGON project. Users input the required information to instantiate a district scenario. The centralised district model (The PENTAGON model) is then queried by project partners to carry out their individual prediction, optimisation and simulation functions. Once again, many of the concepts semantically captured within Figure 7.2 are utilised within the optimisation case studies demonstrated in Chapters 5 and 6. The purpose of this section is to demonstrate that

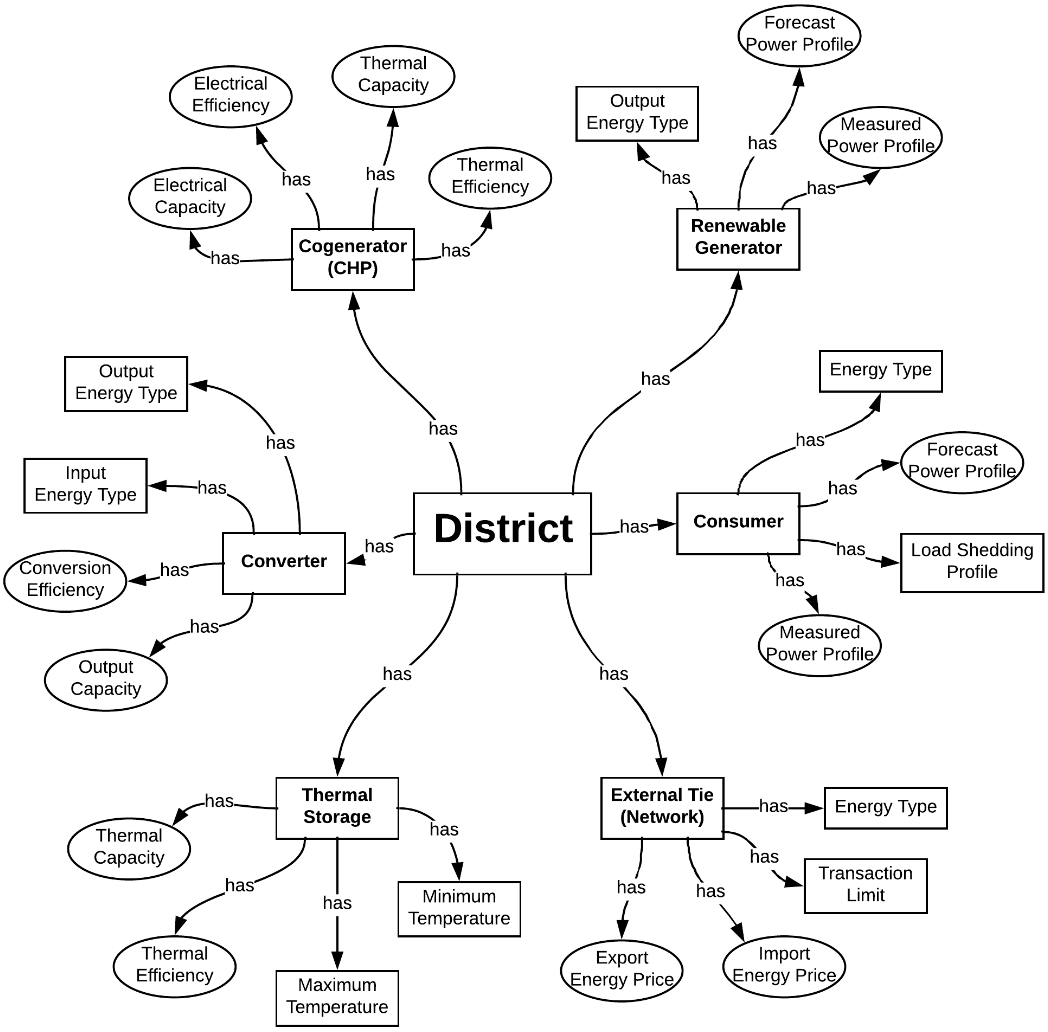


Figure 7.2: An illustration of district-level objects and concepts and the relationships between them. Oval indicates that it is used in Chapters 5 and 6, rectangle indicates an additional concept.

whilst formalised semantics have not been used in the energy management strategies presented in this thesis, there are many projects and researchers that have formally defined the required concepts within ontologies. This would allow a more scalable, extensible, and interoperable foundation from which the optimisation methodologies demonstrated in this thesis could be deployed. Existing, generic ontologies such as the Semantic Sensor Network (SSN) can then be re-used and linked with the more bespoke domain-level energy models.

7.3 A Semantically Enabled Platform

The semantisation of building and district-level energy concepts and objects through linking on domain-level and meta-ontologies has been discussed in

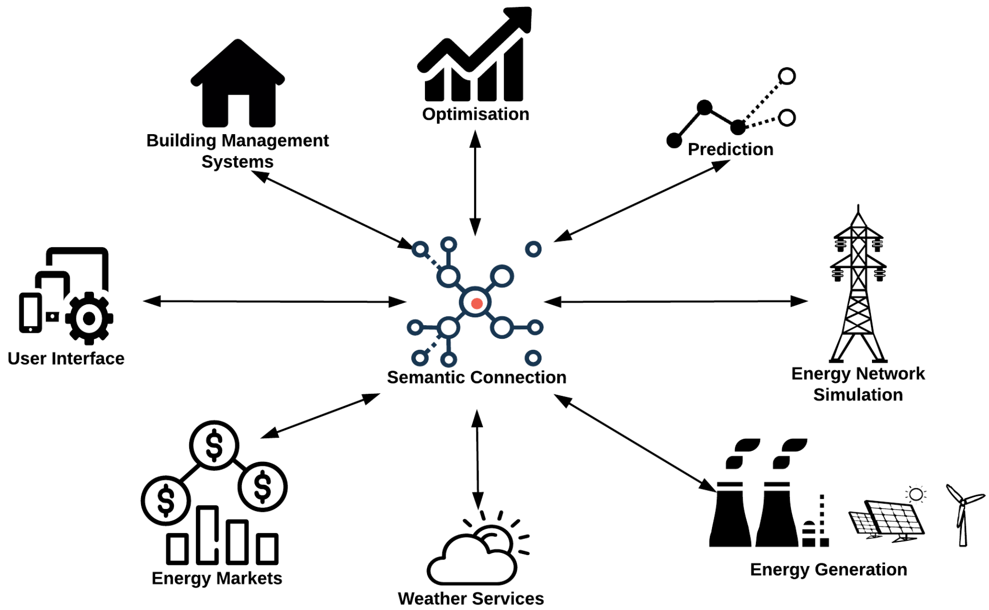


Figure 7.3: An integrated, smart energy management platform underpinned by semantic interoperability

Section 7.2. Much of the required information could come through linking BIM, energy models and BMS. The domain-level ontologies achieved in European projects such as RESILIENT and KnoHolEM alongside recent PhD projects, show promise to facilitate more integrated, holistic management of energy and smart cities. This can aid management across different domains such as water, energy and transport which are traditionally considered in isolation. Common semantic descriptions can help to link data that has previously been siloed within just a single domain. Essentially, the ontology can serve as the central, coordinating brain to link the heterogeneous data, technologies and descriptions across domains to provide a more comprehensive view of the complete system. This can be exploited to build a holistic platform for smart energy management and beyond.

Specifically in the context of the work carried out in this thesis, Figure 7.3 shows the potential structure of the platform required to integrate the heterogeneous data resulting from several distinct modules. This is inspired and informed by the authors literature review, original work detailed in this thesis, and experience working on multi-disciplinary research projects. Here the role of each module will be discussed and the benefit of a platform based on a shared semantic model will be outlined.

- The **weather services** module would utilise existing API to access local weather forecasts for the following 24 hours and beyond. Whilst prediction of outdoor temperature, pressure and relative humidity is commonplace from modern weather services, some interpolation and data manipulation may be required in addition. Weather forecasting services rarely provide predictions with a 15 minute granularity and are likely to relate to a specific weather station. In particular, the prediction of solar radiation is challenging and not commonly provided by weather services. Solar radiation may have to be predicted utilising alternate variables such as forecast cloud cover and outdoor temperature.

- **Prediction** through machine learning techniques has been integral in the methodologies developed throughout this thesis. Due to the extensive amount of data that could be retrieved and stored in a database due to semantic interoperability, advanced machine learning techniques are highly applicable. The forecasting of energy demand and solar PV generation have been deployed in this thesis but could be extended to cover additional renewable energy sources such as wind power and solar thermal. In addition to providing forecasts of energy demand and supply, the prediction module could also be used to identify component failure. If expected predicted values consistently deviate from measured outcomes, this could indicate necessary maintenance far earlier than the issue would otherwise have been discovered.

- In addition to forecasting energy demand and generation, it may be necessary to carry out some level of **energy network simulation**. For heating, this would come via the form of a district heating model. It is necessary that the optimisation is aware of the thermal lag and losses within the distribution network as well as the constraints on the amount of heat that can be delivered at any one time. Similarly for the electricity network, there are clear grid constraints enforced by the TSO such as peak capacities at each electrical bus and substation. Although not normally a feature in typical energy configurations, the gas network may need to be modelled if bi-directional gas exchange becomes permissible and power-to-gas technology becomes prevalent.

- To allow the proposed energy management platform to implement decisions and assess the result of their actions, an effective link must be in place with **building management systems** and **energy generation** controllers. It would be expected to utilise existing sensors to read features such as indoor temperature or the status of specific devices. The connection should also be bi-directional to send optimisation decisions made within the platform to be implemented by the physical actuators and controllers managed by these existing systems.

- As energy networks become more decentralised, a semantic connection to the **energy markets** will take much greater significance. It is expected that energy markets will become increasingly deregulated and more competitive, with new entrants offering more dynamic ToU tariffs due to the roll-out of smart meters. In the near future, there may be additional opportunities for local, inter-district, energy trading based on local energy surpluses. To inform the optimisation decisions, real-time energy prices will be essential.

- By semantically linking the wealth of information from the previously discussed modules, a more complete vision of the contextual circumstances is achieved. This would allow an **optimisation** module to make more informed decisions to be applied to specific energy system. The optimisation module itself could use any appropriate methodology and solver for each case study. This should be made simpler by the solid foundation provided by the underpinning semantic model of the systems.

- The entire purpose of the proposed platform should be to make the job of a facility manager simpler. Therefore a clear, interactive and visual **user interface** should be provided and built on top of the semantic platform. Several, simple, KPI's should be defined to see the benefit of optimisation decisions in regards to energy, cost, emissions and user comfort. It may also be beneficial to develop a 3D visualisation of the case study district in situ on a wider map of the area. The semantic descriptions of critical components within the district could allow location prompts if the data demonstrates a component failure. Alerts such as this can allow facility managers to more quickly identify and resolve system failures.

7.4 Digitisation of the Built Environment

An additional factor that feeds into the capability of the semantic platform described in Section 7.3, is the increased digitisation of the built environment. This comes from several different angles. At a building-level there is legislatory pressure to produce BIM representations of new or retrofit buildings. Ideally, these models will contain a very high level of detail down to descriptions of individual components and devices. This would require a paradigm shift to not only develop BIM at the design stage but also maintain the models during the operational phase of the building life cycle. This high level of detail could then be utilised by a semantic platform when systems fail or when equipment is upgraded.

Whilst BIM models are largely available for new builds, a major challenge exists to generate BIM models for older existing buildings. Within Chapter 4, a 3D laser scanner was used to generate an as-built representation of an existing building. The 3D scanners produce an output in the form of a point cloud which, in of itself, has little meaning. The point cloud must be utilised and converted to a digitised BIM representation of the building. Currently, this process is highly manual and time consuming. However, this challenge has formed an active and growing research field targeting the direct, automatic, generation of BIM models from a point cloud. If a viable solution to this problem can be found, it is feasible to expect increased digitisation of existing buildings at a much wider scale.

Development of accurate energy models is, if anything, a more pertinent task than the creation of BIM models for the control methodologies outlined in this thesis. The most significant challenge standing in the way of the deployment of the proposed control methods is the generation of surrogate energy models. Throughout this thesis, a building energy simulation model was developed and used to generate training data from which a machine learning model could accurately replicate the behaviour of the case study building. It is the authors hope that building energy models become more widely available in the future.

Currently, there is limited provision for the exporting of BIM models to building energy simulation packages. Often an entirely new model for energy analysis needs to be developed in parallel to the BIM model and both models would require updating throughout the life cycle to ensure consistency. The ultimate solution to BIM and building energy simulation interoperability, is the development of a single software package that contains modules for both types of modelling based on a single, central model. This is beginning to happen with the inclusion of energy analysis packages within one of the most popular BIM software, Autodesk Revit. However, this solution has some way to travel before acceptance as the norm within the industry.

In addition to building-scale modelling efforts, some researchers are developing methods to generate city-scale, 3D models. In order to enable district, or city-scale energy management, key characteristics and locations of important components should be captured. Modelling efforts found in existing research range in their detail and rendering from block shaped details to visually accurate recreations. However, there is a requirement to develop something beyond a 3D Google maps for the urban model to be relevant in energy management. A true urban energy model must have additional information semantically linked to the 3D visual representation of the building.

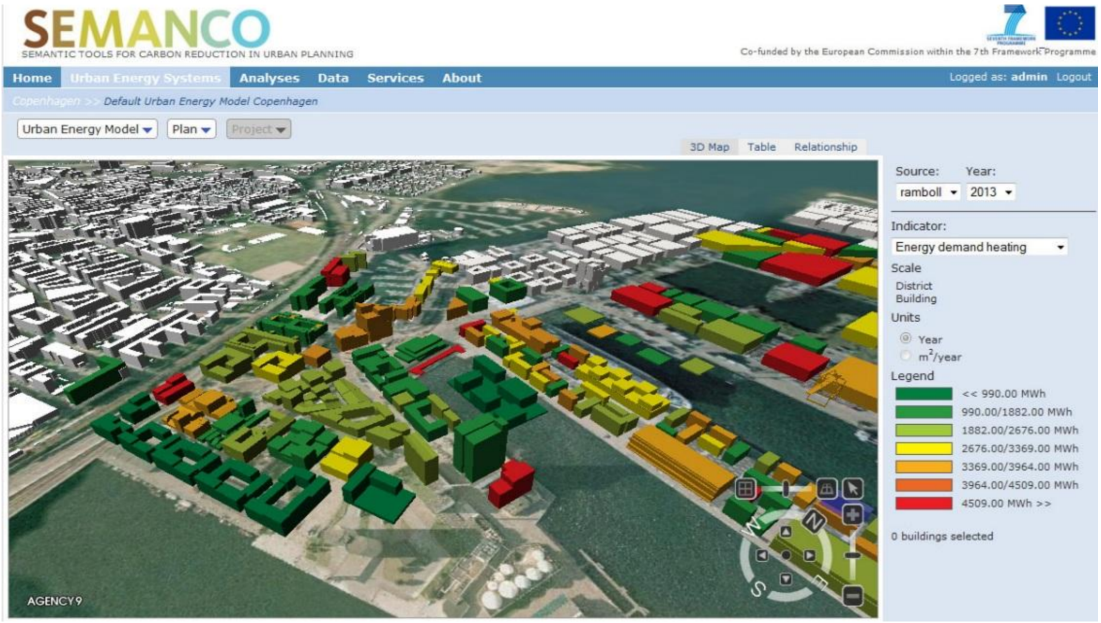


Figure 7.4: The SEMANCO interface demonstrating and urban model of Copenhagen with a heating demand layer [347]

Several research projects and data structures have aimed to tackle this challenge including SEMANCO[1], OPTIMUS[2], and CityGML[3]. Energy consumption and generation can be linked to individual buildings to efficiently generate useful information for urban planners. An example developed in the SEMANCO project is shown in Figure 7.4. A similar interactive view could form the basis of the user interface of the semantic platform described in Section 7.3.

7.5 The Rise of Artificial Intelligence

The proposed semantically enriched platform could provide the ideal basis on which artificial intelligence applications could be built. Throughout this thesis, relatively simple, back-propagation ANN were used to carry out all predictions. This technique was chosen as it has been used extensively in the literature, is relatively well understood for these applications, and has been shown to perform well for the category of tasks required in this thesis. However, artificial intelligence and machine learning has a significant research field of its own that is constantly refining and developing new methods. A complete appraisal of machine learning methods was beyond the scope of this research, but it is expected that more advanced methods such as deep learning, random forest and ensemble learning techniques could provide slightly better prediction performance in the near future.

[1] http://www.semanco-project.eu/
[2] http://www.optimus-smartcity.eu/
[3] https://www.citygml.org/

An alternative method of energy modelling that could overcome the challenges of model development outlined in Section 7.4 could also come from developments in artificial intelligence. An extensive store of labelled and well-defined data that could be provided by a semantic platform could aid the deployment of unsupervised machine learning applications. As opposed to the supervised machine learning deployed in this thesis, unsupervised machine learning methods are unguided. They are not given specific inputs to trial, instead they are free to draw inferences from all available data. This could lead to a more ‘plug and play’ approach where applications are simply given access to the collected data relating to a building, district or city and would require no further manual intervention beyond validation.

An unsupervised approach would require some time to learn the appropriate relationships and refine its performance but would significantly reduce the human effort of modelling, which as discussed in Section 7.4, is a significant limiting factor. An additional advantage to unsupervised approaches would be their ‘always learning’ nature. They should be constantly re-assessing data and aiming to continually improve. This partially overcomes one of the traditional drawbacks of data-driven, black-box, modelling; the problem of modelling a system that changes over time with the addition of new components or varying user behaviour.

With the increased growth in IoT devices throughout consumers homes, it is reasonable to expect that the near future will present near-unbounded opportunities for additional AI applications. IoT controlled lighting, blinds, appliances, heating and cooling are already available commercially. It will therefore be possible to disaggregate building energy consumption to specific zones and devices to potentially allow a much finer control. In the context of this thesis, the zone-level heating controller presented in Chapter 4 could be enabled by a smart home IoT platform which links data from several sensors an heating device. The optimisation strategy could then be deployed on top of this platform, retrieving all the required semantic information from it.

As the number of interconnected energy consuming devices grows the number of potential innovations and opportunities will also grow alongside it. Example applications stem from the deployment of IoT smart meters, these will allow the implementation of more dynamic ToU tariffs that could allow savvy consumers to reduce their costs and aid the balancing of the grid. IoT could also be deployed to enable ‘Vehicle-to-grid’ technology where the car battery could effectively be rented by the DSO for load balancing services when plugged in. The diversity of potential application could lead to greater interoperability, allowing simultaneous, holistic control of several domains.

7.6 Summary

This Chapter has primarily aimed to answer research question 5:

Can a semantic web approach ease the deployment of advanced energy management strategies on a wider scale and aid integration with additional domains?

This Chapter has drawn from previous and ongoing research that the author has been exposed to. Through discussion of these ideas, and providing example ontological structures of building and district energy components, it aims to demonstrate the role that semantic web technologies can play. In the authors opinion, the energy management strategies demonstrated in this these should be underpinned by a comprehensive common ontology similar to that already developed in projects such as KnoHolEM. From this base, a semantically-enabled energy management platform could be constructed that incorporates a wide range of modular services. By its very nature, this would provide a more scalable and holistic solution, that could be adapted and improved over time to incorporate additional domains. Any future management platform must be context-aware by considering factors such as real-time energy tariffs, stochastic energy generation, occupant comfort and weather conditions. Whilst the optimisation methods developed throughout this thesis may not be the finished article, they go some way to achieving these characteristics and demonstrate the clear added value of a more holistic and context-aware approach to energy management.

This chapter has also aimed to outline wider areas of research and trends that combine and build upon the work carried out in this thesis. By outlining these evolving research fields, the relevance of the energy management methodologies developed in this research should become more relevant to practitioners. Alongside the evolving energy landscape, there is significant growth in the power and usage of AI techniques. New algorithms could enable significant improvements in prediction performance and limit the requirement for expert users to select pre-defined predictors through unsupervised learning. Increased requirements for digital representations of buildings and the wider scale modelling of cities for smart city projects have the potential to provide vital information to dovetail with the proposed semantic platform. The greatest potential source of innovation lies with the growth of IoT devices within homes and beyond. The benefits of integrating these data sources could revolutionise the way energy is managed. It is expected that this new wealth of data could provide an active source for the development of new and existing AI applications.

8 | Conclusion

This Chapter will re-visit the research questions provided in Chapter 1 and summarise the work done to answer them. The exploration of each research question will combine together to be able to address the main hypothesis at the centre of this research. Following this, a summary of the key contributions to the body of knowledge will be provided. The limitations of this work will be identified and discussed. Building on this discussion, future areas of research that can build on the work carried out in this thesis are outlined.

8.1 Main Research Findings

This section aims to answer the central research hypothesis which was outlined in Chapter 1. In order to test this hypothesis, four, more specific, research questions were developed. Therefore each research question will be re-stated and addressed consecutively in specific sections. This will be followed by a final discussion on the research hypothesis.

8.1.1 Modelling for Operational Optimisation

The first research question was:

How can the components found within a district energy system be modelled for the purposes of operational optimisation?

This research question was largely the target of Stage 1 of the research methodology. A thorough review of building and district-level optimisation strategies led to the conclusion that for real-time, operational optimisation, accurate yet computationally simple prediction models needed to be used. Therefore, the key criterion when assessing the modelling methods outlined in the literature was their applicability for use in real-time control. This largely ruled out any complex, white-box modelling techniques as they take too long to solve and often require a high-level of expertise to develop.

The alternative to white-box modelling methods comes from purely data-driven, black-box models which have no understanding of the physical systems they aim to replicate, or from grey-box modelling techniques which often contain simplified physical models with several parameters that need to be tuned using a small amount of training data. Throughout the literature review carried out in Chapter 2, it was shown that machine learning models have been extensively applied to various components within the energy sector and have achieved a high accuracy. Therefore, the literature review concluded that machine learning models could be used to model solar PV, solar thermal, building energy demand (electrical and thermal), wind power generation and heat pumps. It is likely that boilers and CHP could be modelled well by polynomial regression curves to capture part load factors often overlooked in optimisation studies. If solar radiation is well predicted then simplified, solar equivalent circuits could also provide a robust modelling method as an alternative to machine learning models. Given that power-to-gas technology is a relatively new and emerging technology, very few modelling methods have been produced in the literature. Studies that do consider power-to-gas tend to provide feasibility studies over a long period of time rather than operational optimisation and hence the modelling is highly simplified as a constant conversion efficiency between input power and output gas. The extensive review carried out in Stage 1 has informed the choice of modelling methods throughout the remainder of this research and provide the foundation for the optimisation and control methodologies developed in Chapters 4 to 6.

8.1.2 Optimisation of Building Energy Demand

The second research question was:

Can predictive control of building energy demand with consideration of external factors lead to reductions in energy cost and improve demand-side flexibility?

Following the research gaps identified in Stage 1 of the research methodology, the next stage of research targetted the development of an intelligent building controller. Building on experience gained during participation with the PERFORMER project, a case study building was modelled in detail using the building energy simulation software Design Builder (which uses EnergyPlus as a simulation engine). The ethos behind the optimisation methodology was to create a ‘thinking’ and adaptive controller that does not simply follow the same pre-defined rules every day regardless of context. The baseline scenario models a typical thermal energy control strategy, setting the heating set point temperature as 21°C during occupied periods and 12°C during unoccupied periods. Furthermore, this is managed by a central thermostat and applies this strategy across all zones within the building regardless of zone-level occupancy patterns.

In contrast, the control strategy developed in Chapter 4 optimises building set points at a zone-level. It considers the predicted weather and occupancy details over the following 24-h and develops a bespoke heating set point schedule for that specific zone under those specific conditions. It achieves this through a genetic algorithm-based optimisation with an internal model of building behaviour using an ANN. The GA trials thousands of potential solutions, utilising the ANN to predict the energy consumption and indoor temperature resulting from each solution, to gradually converge towards a (near) optimal solution. The optimisation is applied to each zone in parallel to reduce the computational time to less than 10 minutes. The control methodology has been shown to be flexible to operate as day-ahead optimisation or MPC, and to minimise energy consumption or energy cost under a ToU tariff.

The optimisation results provided in Chapter 4, clearly demonstrate the benefits of a predictive, adaptive, and context-aware building controller over the static, reactive, rule-based controller used in the baseline scenario. Through a combination of gradual pre-heating, exploiting afternoon solar gains, and only heating zones when required, the optimisation was able to reduce energy consumption by around 18% without breaching the thermal comfort constraints. When operating under a ToU tariff, the optimisation demonstrated an ability to consider the energy prices and shift heating demand to cheaper consumption periods. This led to an increase in energy consumption compared to the energy minimisation, but managed to produce greater cost savings of around 23%. From this evidence, it can be concluded that by providing a wider vision to a building controller it can achieve greater flexibility and benefits to the consumer, hence answering research question 2.

8.1.3 Optimisation of District Energy Supply

The third research question was:

Can taking an optimisation-based approach to the control of district heat generation improve upon existing rule-based priority order strategies?

Having demonstrated the potential flexibility and savings that could be achieved by developing a more intelligent building-level controller, focus then turned to district-level energy management. In a decentralised energy system, there may be several energy conversion technologies available to produce the energy required by end users. So the core question facing a facility manager is which conversion technology should be used at what time? During Stage

2 of the research methodology, the energy management decisions of facility managers applied to decentralised energy systems has been evaluated. Traditionally facility managers have conducted static calculations to determine the cost of each technology alongside technical constraints to produce a priority order strategy. In the case study outlined in Chapter 5, a simulated district energy system was developed containing a CHP, heat pump, gas boilers, thermal storage, solar PV and 5 buildings of different use types. The baseline control strategy was to use the CHP first, then if the heat demand was greater than the CHP heat output, use the heat pump, and finally use the gas boilers.

Whilst the baseline control method provides a simple and relatively effective solution, static calculations of the cost of generation have a several fatal flaws. In a multi-vector district energy system, the determination of static costs becomes much more complex. For example when computing the cost effectiveness of the CHP, one must determine the value associated with the electrical component of its output. The electricity has variable prices when sold to the grid, sold to local consumers or provided as an input to a heat pump. This is both highly contextual and dynamic. In a district energy system with stochastic renewable resources such as solar thermal or solar PV, the dynamism and variability within the district becomes increasingly pronounced. Furthermore, static methods fail to utilise the flexibility contained within thermal storage tanks and the possibility to shift load from one period to another to minimise cost to the energy centre. Therefore, the control strategy developed in Chapter 5 uses an optimisation-based approach to select the schedules of the available energy conversion technologies at each hour of the day depending on the demand at that instance and the available renewable supply. Once again, the optimisation strategy uses the combination of a GA and ANN to predict district energy demand and renewable energy supply.

The performance of the optimisation-based approach gives a significant improvement over the baseline control strategy. By allowing a controller to deviate from static, priority order rules, the optimised solution aims to balance the electrical output of the CHP with the electrical input to the heat pump. This results in less electricity sold to the national grid at a relatively low price and instead utilises it locally to produce the required heat energy for the district. The optimisation also fully utilises the thermal storage tank by charging during the early mornings, midday demand trough, and the evening. It then deploys the stored energy during peak periods to displace gas boiler usage which is the costliest producer. The district supply-side optimisation leads to a 45% increase in profit to the district energy centre whilst also reducing CO_2 emissions by 3.75%. This provides clear evidence that a predictive, optimisation-based approach can provide significant benefits to a facility manager compared to a traditional rule-based approach, hence providing a positive answer to research question 3.

8.1.4 Combined Supply and Demand Energy Management

The fourth research question was:

Can integrated, holistic control of both energy supply and energy demand lead to greater economic and environmental benefits than independent control?

The work completed in Chapters 4 and 5 demonstrated that building and district energy management can react and adjust to external conditions and both benefit from increased flexibility. The final research question is tackled in Chapter 6 using the same district case study that was outlined in Chapter 5. To answer this question the supply-side optimisation was expanded to not only control the CHP, heat pump, gas boilers and thermal storage but also manage the energy demand via the heating set point schedule of the office building. The management of building thermal demand is much the same as that developed in Chapter 4, however, the set point is applied at a building-level in this scenario to reduce the number of optimisation variables. The office building alone is selected as a building of this usage is likely to be most flexible to external temperature control in comparison to a hospital, hotel, or residential buildings.

The optimisation operates in much the same way as the previous Chapters, but the hypothesis being tested in this scenario is whether including the flexibility of the building demand can aid the optimisation of the energy supply and reduce the costs (or increase the profit) to the district as a whole. A full and fair comparison can be made, having run the optimisation strategy over the same test week under the same conditions as the supply-side only optimisation. The optimisation shows a consistent pattern of trying to shift building load from the morning and afternoon peaks to the middle of the day where district energy consumption as a whole is lower and hence cheaper. This effort in conjunction with the optimisation of energy supply and thermal storage usage led to a 53% increase in profit compared to the baseline scenario. This is an 8% increase compared to optimisation of the supply-side alone and provides the lowest CO_2 emissions of all scenarios, 4% lower than the baseline. Despite the office building consuming a similar amount of energy compared to the baseline scenario, the flexibility it was able to provide in terms of load shifting in coordination with the district energy supply gave clear benefits to the district. The multi-scale, supply and demand control adopted in Chapter 6 clearly demonstrates the potential benefits of a more integrated and holistic energy management approach, providing positive confirmation towards research question 4.

8.1.5 Scalability and Interoperability Through Semantics

The final research question was:

Can a semantic web approach ease the deployment of advanced energy management strategies on a wider scale and aid integration with additional domains?

To address this research question, a discussion-based approach was used in Chapter 7 to assess trends in additional research fields. It aimed to analyse how the energy management solutions proposed in this research could be implemented more widely. This Chapter demonstrated the how semantic web technologies could be applied to capture and model the information required to implement the proposed optimisation strategies. It presents the relationships between different concepts and demonstrates that many of these are already captured in by BIM. It therefore stands, that if the availability and quality of BIM models continues to grow, that these could provide the semantic foundation on which a more scalable and interoperable semantic platform could be built. The semantic platform proposed in Section 7.3 is a more modular arrangement largely based on the optimisation methodologies described throughout the thesis with some additions. This approach is inherently more scalable and adaptable and is facilitated by the semantic base which ensures developers share a common description of components within a complex energy system. As other domains become increasingly linked to building and district energy systems (such as transport), the platform has scope to incorporate these changes through the mapping of domain ontologies and the addition of modules.

8.1.6 Revisiting the Hypothesis

The discussion surrounding the four research questions has laid the basis for a final evaluation of the main research hypothesis which is re-stated here as:

"Simultaneous control of building and district energy systems can achieve greater energy savings and environmental benefits by operating cooperatively and increasing their awareness of external, contextual building information such as weather conditions, occupancy, energy generation, or energy prices."

At each stage in this research, the complexity of each case study has been gradually increased. Initially, the building optimisation methodology just has access to weather forecasts and produced an optimal heating set point schedule based on that information. Then, occupancy at a zone-level was introduced to produce bespoke zone-level heating strategies. Following that, the optimisation was adapted to minimise energy cost under a ToU tariff. At each stage, the greater the number of variables provided to the optimisation, the greater the performance gain compared to the baseline. This demonstrates that as you increase an adaptive controllers awareness of its surroundings, it can make more informed decisions, and hence produce greater benefits. By optimising based on the individual context of a specific circumstance, performance can be improved significantly compared to rule-based controllers.

The next evolution of the research, targetted district-level, supply-side control. Once again, it started from a position that better solutions were available that the generic, rule-based, priority order strategy that is used by facility managers. The developed, optimisation-based approach using predictive management, was able to significantly increase the operational profit achieved by the energy centre through exploration of less intuitive solutions such as purchasing more electricity from the grid, and reducing the amount of electricity sold. The controller was made aware of external factors such as the weather and energy tariffs. It used the weather forecasts to produce predictions of renewable energy generation and district heat demand which aided the optimisation when making its generation and storage decisions. The case study results produced in Chapters 4 and 5 clearly demonstrate that providing addition of contextual information can greatly improve the performance of an energy management solution.

The culmination of this research effectively combined the building-level optimisation carried out in Chapter 4 with the district-level optimisation conducted in Chapter 5 to simultaneously manage both energy supply and demand. The case study results produced by this holistic optimisation approach, demonstrated that by working cooperatively, significant cost and environmental savings can be achieved. By allowing the controlled building to work in conjunction with the district energy centre to shift loads away from high demand periods, a significant reduction in gas boiler usage was achieved. The consequence of this load shifting could have wide-scale benefits to the entire district, as district demand can be fulfilled at lower costs. The combination of the results demonstrated throughout this thesis, clearly confirm the central research hypothesis to be true.

8.2 Contribution to the Body of Knowledge

The contributions resulting from this thesis relate to the development of a building-level and district-level energy management controller discussed in Chapters 4 and 5 and culminate in the contribution resulting from their summation in Chapter 6. The contributions from each Chapter were provided in each of these Chapters respectively. However, they will be re-stated here to illustrate the contribution from this thesis as a whole.

At a building-level:

- A predictive, zone-level, thermal building controller was developed taking into account weather forecasts, occupancy and energy tariffs.
- This was achieved through combining a genetic algorithm with internal, ANN prediction models to estimate indoor temperature and energy consumption.
- The optimisation strategy was flexible enough to operate as day-ahead optimisation or MPC, and to minimise energy consumption or energy cost.
- The zone-level optimisation reduced energy consumption by 18% and energy cost by 23.5% compared to the static baseline control scheme.

At a district-level:

- A district-level, heat load generation controller was developed to maximise profit to the central energy centre whilst fulfilling district heating demand.
- All key variables such as renewable energy generation and district heat demand were predicted in real-time using ANN.
- The methodology was able to incorporate non-linear, part-load characteristics associated with CHP's and gas boilers.
- A real-time, error management, adjustment algorithm was introduced to allow the controller to react to forecasting errors.
- The optimisation methodology led to a 45% increase in profit and a 3.75% reduction in CO_2 emissions.

Combined at a building and district-level:

- A combined methodology to simultaneously control both building energy demand and district energy supply was developed.

- This optimisation is capable of operating at multiple scales simultaneously, i.e. at building and district-level.
- A clear and direct comparison against a supply-side only optimisation illustrates the benefits of utilising building as a source of demand flexibility.
- This methodology led to a 53% increase in profit to the energy centre compared to the baseline scenario.

8.3 Limitations and Future Work

Despite the contributions made during this research, the developed energy management solutions have a number of limitations and should be considered in future work. Many of the limitations are related to the modelling assumptions made throughout the thesis. A number of simplifying assumptions are to be expected when formulating an optimisation problem to allow it to be solved. Where possible, effort was made to include part-load characteristics of heat generation technologies, however, the simple input-output relationships would need to be verified against actual performance.

The thermal storage tank was modelled to have a constant energy loss of 5% when charging or discharging. In reality, it is likely that the losses from the tank would vary depending on tank temperature and external temperature. The distribution network was not explicitly modelled due to a lack of original data. The inclusion of distribution losses and propagation time could only be modelled with indefensible arbitrary values. Hence, they were not included in this work and investigation of these factors was considered beyond the scope of this thesis.

It is proposed that these modelling limitations can be overcome in future work with integration of the optimisation methodologies with the semantic platform discussed in Chapter 7. The modular nature and use of a shared ontology fosters interoperability between different simulation and prediction packages. Therefore, when data becomes available from pilot site partners, more detailed simulation models can be developed and utilised by the optimisation strategies developed in this thesis. The optimisation algorithm (GA) used throughout the energy management strategies is completely flexible to incorporate any external models as it requires no knowledge of the mathematical operations being conducted within the model itself. The optimisation simply requires the numerical output of any simulation model. As a specific example, this could include a detailed model of a district heating network modelled within software such as TRNSYS or Simulink. Naturally, this level of advance modelling requires data from a real pilot site for calibration purposes and to provide validation. Complete validation of the energy management strategies proposed in this thesis can only be achieved through deployment at real pilot sites.

This thesis does not aim to investigate the performance of different machine learning algorithms or optimisation algorithms. A GA and an ANN was chosen due to their frequent use throughout the studied literature. However, within their fields, these algorithms are relatively old. Future work could trial different, more modern, machine learning techniques such as deep neural networks or random forests. In terms of optimisation, algorithms such as particle swarm, ant colony, or memetic algorithms could be tested. The discovery of improved algorithms would enhance the energy management strategies provided in this thesis. An additional point of future work is to make an assessment of the effect of weather forecasting errors. Throughout this thesis the weather forecast was assumed to be completely accurate. In reality, this will contain some small error. The impact of these errors on the machine learning prediction should be quantified to provide greater stability within the energy management strategies. It is expected that when weather forecasting errors are considered the benefits of an MPC approach will become more clear.

Finally, it will be important to develop a decentralised version of the energy management strategies given in this research. Ideally, the decentralised optimisation would be benchmarked against the centralised approach for the same case study district. If comparable performance is found, then a decentralised optimisation is likely to be more applicable in the future. It would be fully scalable to include as many consumers and generators as required with no limitation on decision variables. It would also give end-users greater control on their own systems and appliances compared to a centralised approach.

8.4 Final Remarks

The common theme throughout this research was to demonstrate that improvements can be made upon static, rule-based controllers. Whilst these rules may perform well in most circumstances throughout most conditions, they cannot provide the best solution in all scenarios. To overcome this, adaptable, context-aware and ‘thinking’ controllers have been developed and applied to the challenges of building energy management, district energy management and finally a combined building and district optimisation. This thesis has demonstrated that a holistic, cooperative, optimisation-based approach is superior in terms of both energy cost and environmental emissions. In the future energy landscape in which energy is increasingly dynamic and decentralised, innovative energy management solutions will become increasingly important.

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