Balancing of Intermittent Renewable Generation in Smart Grid

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I would like to dedicate this thesis to my loving parents,
Regina and Algimantas Gelažanskai…

Declaration

I, Linas Gelažanskas, hereby certify that this thesis has been written by me and has not been submitted in any previous application for a higher degree. The work presented here was carried out at the University of Lancaster between August 2012 and January 2016.

Date .... Signature of candidate ....

I, Dr. Kelum Asanga Akurugoda Gamage, hereby certify that the candidate has fulfilled the conditions of the resolution and regulations appropriate for the degree of Doctor of Philosophy in the University of Lancaster and that the candidate is qualified to submit this thesis in application for that degree.

Date .... Signature of supervisor ....

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Abstract

This thesis researches a novel electricity demand response method and renewable energy management technique. It demonstrated the use of flow batteries and residential hot water heaters to balance wind power deviation from plan.

The electricity supply-demand balancing problem becomes increasingly more difficult. A large portion of complexity to this problem comes from the fact that most renewable energy sources are inherently hard to control and intermittent. The increasing amount of renewable energy generation makes scientists research new supply-demand balancing possibilities to adapt for the changes.

In this research wind power data was used in most cases to represent the supply side. The focus is on the actual generation deviation from plan, i.e. forecasting error. On the other hand, the methods developed in this thesis are not limited to wind power balancing.

Two major approaches were analysed - heating ventilation and air conditioning system control (mainly focused on, but not limited to, residential hot water heaters) and hybrid power system comprising of thermal and hydro power plants together with utility scale flow batteries. These represent the consumption side or the demand response mechanism.

The first approach focused on modelling the behaviour of residential end users. Artificial intelligence and machine learning techniques such as neural networks and Box-Jenkins methodology were used to learn and predict energy usage. Both joint and individual dwelling behaviour was considered. Model predictive control techniques were then used to send the exact real-time price and observe the change in electricity consumption. Also, novel individual hot water heater controllers were modelled with the ability to forecast and look ahead the required energy, while responding to electricity grid imbalance. It proved to be possible to balance the generation and increase system efficiency while maintaining user satisfaction.

For the second approach, the hybrid multi-power plant system was exploited. Three different power sources were modelled, namely thermal power plant, hydro power pant and flow battery. These sources were ranked by the ability to rapidly change the output of electricity. The power that needs to be balanced was then routed to different power units according to their response times. The calculation of the best power dispatch is

proposed using a cost function. The aim of this research was to accommodate for the wind power imbalance without sacrificing the health of the power plants (minimising load variations for sensitive units).

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Symbols

Acronyms / Abbreviations

AC	Alternating Current
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller test
AGC	Automatic Generation Control
AI	Artificial Intelligence
AIC	Akaike Information Criterion
AICc	Corrected Akaike Information Criterion
ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criterion
BP	Back-Propagation training method
BRELL	Belorussia, Russia, Estonia, Latvia and Lithuania synchronous zone
CH	Canova-Hansen test
DC	Direct Current
DDSM	Decentralised Demand Side Management
DE	Decentralised Energy
DER	Distributed Energy Resources
DG	Distributed Generation

DHW	Domestic Hot Water
DLC	Direct Load Control
DR	Demand Response
DSM	Demand Side Management
EMU	Energy Management unit
EPRI	Electric Power Research Institute
ESS	Energy Storage System
ETS	Exponential Smoothing
EV	Electric Vehicles
FACTS	Flexible AC Transmission Systems
FB	Flow Battery
HPP	Hydro Power Plant
HVAC	Heating Ventilation and Air Conditioning
HVDC	High Voltage Direct Current
IBP	Incentive Based Programs
ICT	Information and Communication Technologies
IED	Intelligent Electronic Devices
KPSS	Kwiatkowski-Phillips-Schmidt-Shin test
LMC	Leybourne-McCab stationarity test
LPF	Low-Pass Filter
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
micro-CHP	Micro Combined Heat and Power

MPC	Model Predictive Control
MSE	Mean Square Error
NAR	Neural Network Nonlinear Autoregressive model
NARX	Neural Network Nonlinear Autoregressive Exogenous model
nMAE	Normalised Mean Absolute Error
nRMSE	Normalised Root Mean Square Error
NTP	Normal Temperature and Pressure
PACF	Partial Autocorrelation Function
PBP	Price Based Program
PID	Proportional Integral Derivative
PMU	Phasor Measurement Unit
PP	Philip-Perron test
PS	Power System
R	Correlation Value
RES	Renewable Energy Source
RMSE	Root Mean Square Error
RTP	Real-Time Pricing
SCADA	Supervisory Control and Data Acquisition
SD	Standard Deviation
SSL	Shiftable Static Loads
STL	Seasonal Decomposition of Time Series by Loess
SVM	Support Vector Machine
TOU	Time of Use
TPP	Thermal Power Plant
UPFC	Unified Power Flow Controllers
WAMPAC	Wide Area Monitoring, Protection and Control

Chapter 1

Introduction

Centuries ago people harnessed energy from the wind, water or muscle. Later, society learned to extract energy and convert to other forms. The increasing demand of power made people go from machines that can replace six horses to today's vast power stations that can do the work of six million horses; the hunger for power has maintained momentum so scientists are looking for new technologies that can generate cheaper, cleaner and more reliable electrical power.

Electricity is one of the major forms of energy that is traded in present society. Advantages of electricity as a form of energy is its speed (travels nearly the speed of light), it is easily transportable over long distances, it is silent and relatively easily transformable to other forms of energy. Green energy technologies allow energy generation without direct pollution to the atmosphere or green house product. Although most of us take electricity for granted, the underlying mechanism of its production are highly complicated. As electricity can not be easily stored in its form, it has to be produced at the exact same time it is consumed. This balancing act between the total generation and consumption requires large amount of resources in terms of coordination, labour, expenses, and technology.

The way electricity is produced globally has not changed much since the invention of the steam turbine, but recent technological advent and concerns about pollution have forced society to move towards green renewable energy sources (RES). It is believed that renewable energy can dominate future energy sector and can be beneficial for health, economy and environment. It is the key to broader energy and climate objectives in reducing greenhouse gas emissions, improving energy supply and security as well as diversifying energy supplies. Countries that pioneer green energy have already proven that it is possible to largely depend on sustainable energy. Figure 1.1 demonstrates that newly installed power plants mainly rely on renewable energy sources. For example Denmark has produced more than 42 % of its electrical energy requirement using wind power alone in 2015 breaking the world record. This coincides with Denmark's goal to reach 50 % of its power consumption from wind by 2020 [DKa12]. UK is another example showing wind power contribution of 11 % of the total electricity generation in 2015. In fact, wind energy has overtaken hydro as the third largest source of power generation in the EU with a 15.6 % share of total power capacity. Germany is the biggest player in wind generation with its share of 44.9 GW of installed wind power [DKs15].

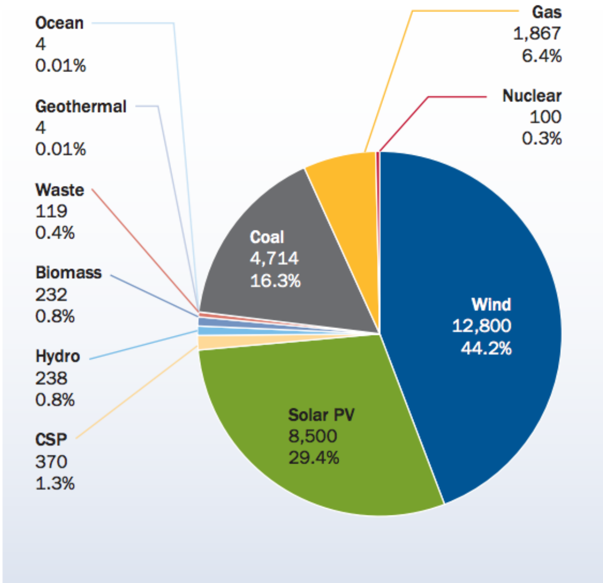

Fig. 1.1 The share of newly installed electrical power capacity in 2015 in EU (MW). Total 28,948.7 MW [DKs15].

On the other hand, renewable energy generation, including wind power has some disadvantages. As a general rule, green energy introduces power variations due to unpredictable intermittent nature and dependency of natural resources such as wind or sun (though some energy sources are intermittent but highly predictable, e.g. tidal energy). Energy management and power distribution problems arise when the actual generation or consumption deviates from plan. It is extremely complicated to accurately forecast solar and wind energy thus there is always a mismatch between the forecasted scenario and actual electricity generation. Disruptions caused by accidents are another source of error. Such forecast errors require costly backup power to cover the emerged imbalance. Alternatively, novel more accurate forecast methods using big data could help to eliminate this problem.

This thesis aims to improve wind power integrity by proposing new energy balancing methods and covers alternative methods to either assist or substitute traditional backup power, both at consumer level and large scale energy storage. The unpredictable intermittent energy should be backed by controllable electric energy consumption devices, e.g. resistive hot water heaters. Firstly, individual hot water forecasting methods are developed for smart hot water heaters. Consequently, these forecasting models are used to develop smart distributed hot water heating system to enable demand response. Secondly, a hybrid mix of conventional generation power units and flow battery power system is developed and analysed for wind balancing capabilities. These methods are proposed to be part of the emerging concept of smart grid.

The research is based on wind generation data gathered from Lithuanian national transmission system operator, and hot water usage measurements in residential dwellings from Energy Savings Trust, London. Computer simulation framework has been setup to analyse wind generation integration. Gridlab-D smart grid simulation environment and Matlab/Simulink software are used to prove the concept.

1.1 Current deficiencies

The current grid operations remain unchanged for many years in the major part of the world. The technological advancement in communications, computational power and sensing needs to be adapted to the electricity sector for more optimal renewable energy integration. In general, there is a lot of room for research and development in the area of Smart Grid.

One of the examples would be the research of implications to the grid when renewable energy sources are connected at the transmission level. The intermittent nature of renewables need to be accounted for, monitored and backed up. Currently there is no clear mechanism to decrease the variability of backup generation that covers wind generation. At the same time, there is a lack of storage in some parts of Europe thus wind generation curtailment is experienced causing high loss in profit. Also, it is widely expected that much of the growth of renewable energy will be based on Decentralised Generation (DG). This might result in additional challenges for distribution network that are not yet fully understood by the scientists [REi14].

Increasing peak demand of energy requires costly infrastructure upgrade. The need for grid expansion can be reduced by balanced geographical distribution of renewable energy sources. Both resource availability and load level need to be taken into consideration. Distributed energy storage promises similar effect to the grid, thus this option needs to be researched. Also, demand response (DR) offers peak clipping and valley filling techniques that would minimise the required upgrades and offer estimated annual savings in the order of €60 to 100 billion in the EU [REi14]. In fact, the costs of grid expansion might offset higher RES generation costs. Overall, recent studies show that demand response is expected to deliver high net benefit requiring only limited costs.

Another technological grid deficiency is the lack of consumer level real-time pricing. Since in most cases there are only two different tariffs throughout the day, the users experience cross-subsidy, i.e. the users who consume electricity during off-peak times often pay more than they should and subsidise the ones that use electricity during high-price times. The implementation of smart metering and real-time pricing would allow users to be charged more accurately and fair.

1.2 Novelties of this research

The overall aim of this research was to investigate, propose and analyse novel wind generation balancing technique to accommodate better renewable energy integration. Throughout the research, the focus was to design a system that requires minimal investment and guarantees that total amount of power from wind generation matches the expected generation pattern. There are two main directions of this research. The first direction of the study includes novel distributed hot water heater control technique to minimise the imbalance effect caused by wind farms, where it shows successful results. Prior to this research no such designs have existed in literature. During the second part of the study, flow batteries in combination with thermal and hydro power plants are used to form hybrid power system that accommodates the need to balance the unpredictable power output by wind farms.

As a starting point, a relationship between price and demand has been analysed prior to developing wind balancing techniques. This complicated dependency has been modelled using artificial neural networks (ANN) for real-time pricing in demand response applications and later served as a very important tool in design of smart hot water heater. Neural network was trained for a group of houses to find the relationship between price of electricity and required cumulative load. The ability to predict different forecast horizons were also assessed. This novel technique demonstrated that price required to reach the required load can be computed at least 30 minutes in advance. It has also been demonstrated that once real-time pricing is applied, the inelastic electricity demand becomes elastic. It exhibits a useful feature of only one-way communication to send the control signal opposed to two-way communication in price negotiation mechanism (price auction).

The proposed novel smart water heater control technique requires tailored individual consumption profiles. Prior to this research there was a lack of forecasting methods for this application in literature. Different forecasting methods have been applied on real world water consumption datasets. The novel ANN model demonstrated better results compared to conventional forecasting techniques analysed in section 4.3, which also showed acceptable results. A novel distributed hot water controller model was then developed using ANN trained by individual historical water consumption data. A number of houses were simulated in a group to demonstrate the ability to respond to the grid needs while maintaining comfortable hot water level. The novel look ahead technique allows to predict future consumption and prepare the exact amount of water required.

As an alternative method to balance electric energy, a hybrid power system that has also been developed in this research consisting of hydro power plant, thermal power plant, flow batteries and wind generation. The main goal of the system was to eliminate the wind generation forecast error by adjusting power output of other power units. The novel technique allows to limit the output rate of conventional power plants to a safe level while additional utility-scale flow batteries absorb high frequency variations. The results show that wind power can be regulated using this technique using a feasible amount of flow batteries.

1.3 Outline of each chapter

This section outlines the following chapters in this thesis. It justifies the selected case studies and the research approaches that were used. Furthermore, it demonstrates how different chapters of this thesis links together.

The work is logically divided into three parts. The first part consists of Chapter 2 and Chapter 3. During overview of the current smart grid technologies in the early stage of this research it has been recognised that one of the biggest intermittent power integration problem is energy balancing. Currently, the balance is achieved by closely monitoring the frequency in the system and signalling fast-reacting power plants to adjust their generation and dispatch the appropriate levels of energy. Unfortunately, intermittent power generators such as wind farms do not offer the possibility to change power output on demand. In addition, the future perspective of the majority of power generated being green (thus intermittent and in most cases not easily controllable) turns the attention to the other side of the energy balance equation - the consumption side. Up to now, the demand control techniques have not been widely researched nor implemented thus this research focuses on user-side related smart grid technologies - mainly demand side management to make the demand elastic.

The preparatory research overviews the current smart grid technologies and performs preliminary work on price-based user awareness and demand response. In particular, this part analyses heating ventilation and air conditioning (HVAC) system and its usage in demand response problems, since it is one of the most energy hungry devices in many parts of the world. Preliminary simulations are carried out to make sure it is possible to significantly change HVAC electricity load using price signal. A GridLab-D model has been created representing the user side and it allowed to understand how much and when the demand can be altered. In addition, this complicated physical model was then simplified by representing electricity price and thermal load relationship using artificial neural networks. ANNs were chosen for their ability to represent nonlinear relationship, for their non-parametric nature and ability to adapt to wide diversity of different input patterns, i.e. a neural network of the same structure can be trained for many to work with many different HVAC usage patterns.

Once the study background has been analysed and preliminary work done, the research continued along two study paths, i.e. part two and part three. Both of these paths attempted to solve similar problem - balancing renewable intermittent power. The second part can be found in Chapter 4 and Chapter 5 and it creates a tool for energy balancing using distributed residential sector, opposed to large scale centralised facilities. It continues and extends the use of ANNs and analyses their forecasting capabilities. In addition, many other forecasting models, such as seasonal decomposition of time series by Loess, seasonal autoregressive integrated moving average and others are compared between each other and the best performing one is used in later work. In this part, the individual hot water consumption profiles are predicted so that the system is able to compute when and how much energy is required. This prediction allows having smart thermal control and timely electrical energy usage. Overall, this section is based on solving the electrical energy balancing problem using domestic smart grid solutions.

Alternatively, the third part of this thesis in Chapter 6 analyses the utility scale approach to the previously mentioned problem using hybrid power systems. As electrical system is very diverse and requires many tools for backup, the same energy balancing problem was addressed from another perspective - industrial large scale energy storage. There are places where electricity is not used for HVAC thus it was decided to also research alternative methods to cover imbalance caused by intermittent wind generation. It combines large scale fast-reacting storage with slow traditional power plants to create hybrid system. All in all, in this research there were two new electricity balancing tools proposed that cover both industrial and residential sectors.

Chapter 2

The main focus of Chapter 2 is to introduce the reader to the subject of renewable power (mainly wind) integrity. It overviews the general concepts of electricity grid, contains literature review and background information as well as the tools required to balance electrical system. New proposed tools are also introduced. Section 2.1 mainly focuses on the concepts, such as centralised electricity generation, renewable energy, electricity balance, smart grid technologies, forecasting and machine learning. It is followed by Section 2.2, in which a paper published in Sustainable Cities and Society journal has been presented reviewing demand side management and demand response concepts in smart grid applications. It also proposes a novel electricity demand control technique using real-time pricing. This preliminary work helps to understand how much energy can be shifted using demand response.

Chapter 3

This chapter contains a paper titled *Neural Network Based Real-Time Pricing in Demand Side Management for Future Smart Grid* that was presented at the 7th IET International Conference on Power Electronics, Machines and Drives (PEMD 2014) conference in Manchester, UK. It proposes an artificial neural network model to understand the relationship between real-time price of electricity and load. In this chapter, a prediction method is presented that calculates a precise price to be sent to the users in order to reach the desired cumulative load of a certain region.

Chapter 4

In order to make use of smart devices that can store thermal energy and to be able to adapt the demand side management methods, it is necessary to understand and model the behaviour and thermal energy usage of residential users. This chapter presents forecasting methods to that can predict hot water consumption at an individual house level. *Forecasting Hot Water Consumption in Dwellings Using Artificial Neural Networks* was presented at the 5th IEEE International Conference on Power Engineering, Energy and Electrical Drives (POWERENG 2015) in Riga, Latvia, and *Forecasting Hot Water Consumption in Residential Smart Houses* published in Energies journal. Both papers forecast hot water consumption in dwellings using different modelling approaches. These models are used in the next Chapter to design smart hot water heater with look ahead approach.

Chapter 5

Energy storage decouples electricity generation from consumption. Distributed hot water storage in residential houses might be the key for a successful demand side management implementation. This chapter contains paper titled *Distributed Energy Storage Using Residential Hot Water Heaters* that was published in Energies journal and analyses the use of existing hot water heaters as distributed energy storage devices to solve the renewable energy intermittency problem. It proposes a novel control technique that forecasts the energy requirements of a particular house and responds to both consumer needs and the system needs (electricity shortage or surplus). The results demonstrate the possibility of saving energy, increasing system efficiency and and resilience.

Chapter 6

This chapter present the content of a paper titled *Hybrid Wind Power Balance Control Strategy using Thermal Power, Hydro Power and Flow Batteries* that was published in International Journal of Electrical Power and Energy Systems. It is an alternative method to the one used in Chapter 5 for balancing electricity on the utility scale. The research shows the ability of a hybrid system to respond to intermittent wind power output. Two types of traditional power generation units are used in conjunction with utility scale modern flow battery storage with the aim of minimising the imbalance, which is caused by the deviation from wind generation plan. A method to calculate the appropriate response times of the plants is demonstrated using a cost function. It also contains an extensive analysis of the battery sizing to fulfil the case study requirements.

Chapter 7

Finally, the last chapter presents a summary and conclusion of the research. It includes key findings, highlights the limitations of the study and recommends future direction of the work.

1.4 Main contributions

This section contains statement of authorship for each multi-authored publication. The leading author of all publications in the main body of this thesis is *Linas Gelažanskas*. Further detailed contributions are described in the following paragraphs.

Chapter 2 through chapter 5 contain five dual-authored articles. In these articles Linas Gelažanskas contributed by proposing the idea, conceptualising the implementation, collecting, analysing and interpreting the data, and drafting the article. Kelum A.A. Gamage critically revised the article and gave advice on the design aspects. Both authors did final approval of the article versions to be published.

Chapter 6 contains multi-authored journal article. Linas Gelažanskas contributed to the work by reviewing existing technology and proposing the hybrid power control strategy, designing and implementing models, collecting and analysing the data as well as drafting the paper. Audrius Baranauskas and Mindaugas Ažubalis contributed by reviewing section 6.2.2. Kelum A.A. Gamage critically revised the article. All authors did final approval of the article before publication.

Appendix B contains multi-authored conference paper. Linas Gelažanskas and Audrius Baranauskas equally contributed to the concept of the novel control strategy. The data has been collected by Audrius Baranauskas. Linas Gelažanskas designed and implemented the models as well as analysed the data and drafted the paper. All authors critically reviewed the article and did final checks.

Authors declare that the main contributions to the articles comprising this thesis are correct.

Linas Gelažanskas ....

Kelum A.A. Gamage ....

Audrius Baranauskas ....

Mindaugas Ažubalis ....

Chapter 2

Background and Literature Review

2.1 Electrical grid background

This section will describe the general concepts of traditional and modern electricity grids, including generation, consumption and balancing methods. It will also include an overview of some forecasting techniques as well as machine learning algorithms that are used in this thesis for demand side management modelling and simulations.

2.1.1 Electrical grid

Today's Alternating Current (AC) power grid evolved from Nikola Tesla's designs published during the War of Currents in 1888. During that period there were large debates whether Alternating Current or Direct Current (DC) were more suitable for large scale electricity grids. Westinghouse Electric Company run by George Westinghouse partnered with Tesla and acquired his patents to be able to create a full AC system. On the opposing side of the front there was Thomas Edison and his Edison Electric Light Company representing the DC electricity system. Thomas Edison and Nikola Tesla are thought to be the main opponents during the battle of currents. Although AC system has proven to have significant advantages over DC system, thus adapted in the major part of the world for transmission and distribution, DC finds its use in High Voltage DC seabed transmission, modern electronics, railway industry, etc. The primary design of electric power system was centralised and unidirectional, consisting of power generation followed by transmission, distribution and consumers at the end of the chain. A bare minimum of monitoring and a demand-driven control was used. Minimal changes have been made to the design of the system since its invention.

The traditional electrical grid can be split into three parts - generation, transmission and distribution. The generation part mainly consists of large power plants that convert various types of energy into electrical energy. It is then passed through an on-site substation onto a high voltage transmission lines that can stretch long distances. Electricity is transmitted to substations in bulk through high voltage transmission lines. Transmission lines, when connected with each other become transmission grid. In UK it is called "National Grid". It consists of several different voltage transmission line types. According to 2015 Ten Year Statement [ten15] there was 11500 km of 400 kV, 9800 km of 275 kV and 5250 km 132 kV or lower voltage transmission line length in the UK. Other voltage levels are seen in different countries. Current implementation includes redundant lines to allow power flow in emergency situations. When a transmission line goes down there is an alternative path for the current to flow. Unfortunately, the majority of tracking and re-routing of power is done manually and causes power disruptions. Usually there are

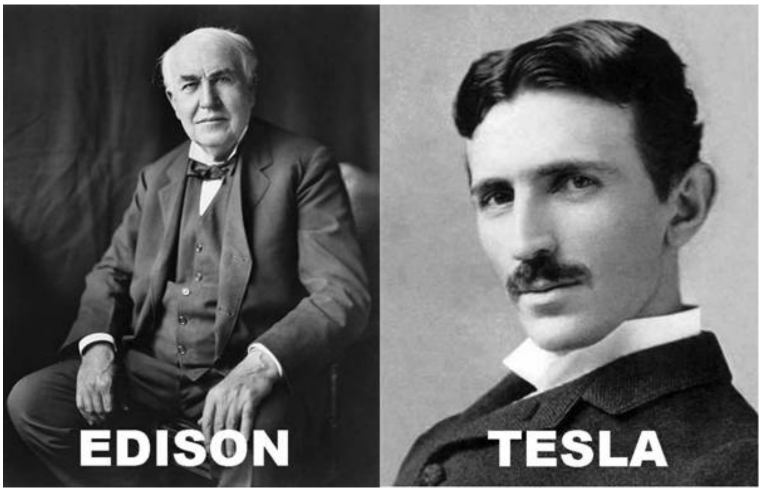

Fig. 2.1 Thomas Edison - American inventor and businessman, proponents of the DC (left),
and, Nikola Tesla - Serbian American physicist, inventor, engineer and futurist, main contributor to the development of AC system (right).

various voltage levels in the transmission system so additional intermediate substations are required.

Once electricity reaches the demand centers, it is passed onto so called distribution network. Distribution system is the last stage of delivering electricity to the end user. It stretches from substation transformer to the socket of end user's meter. Usually it consists of medium to low voltage lines and a series of step-down transformers. There can be couple of end user types: sub-transmission customers (26 kV-69 kV), primary customers (13 kV-4 kV) and secondary customers (120 V-240 V). In the traditional grid design the electricity flows one-way, from large scale centralised generation to a many consumers in a radial fashion. Also the meters may only have two different tariffs – daytime and nighttime. Smart Grid implementation would allow real-time pricing of electricity and the ability to buy and sell electricity. This would create a whole new market where people could "trade" electricity. Figure 2.2 depicts general layout of the electricity networks.

2.1.2 Electric energy generation

This section introduces different types of centralised electricity generation and decentralised energy provision.

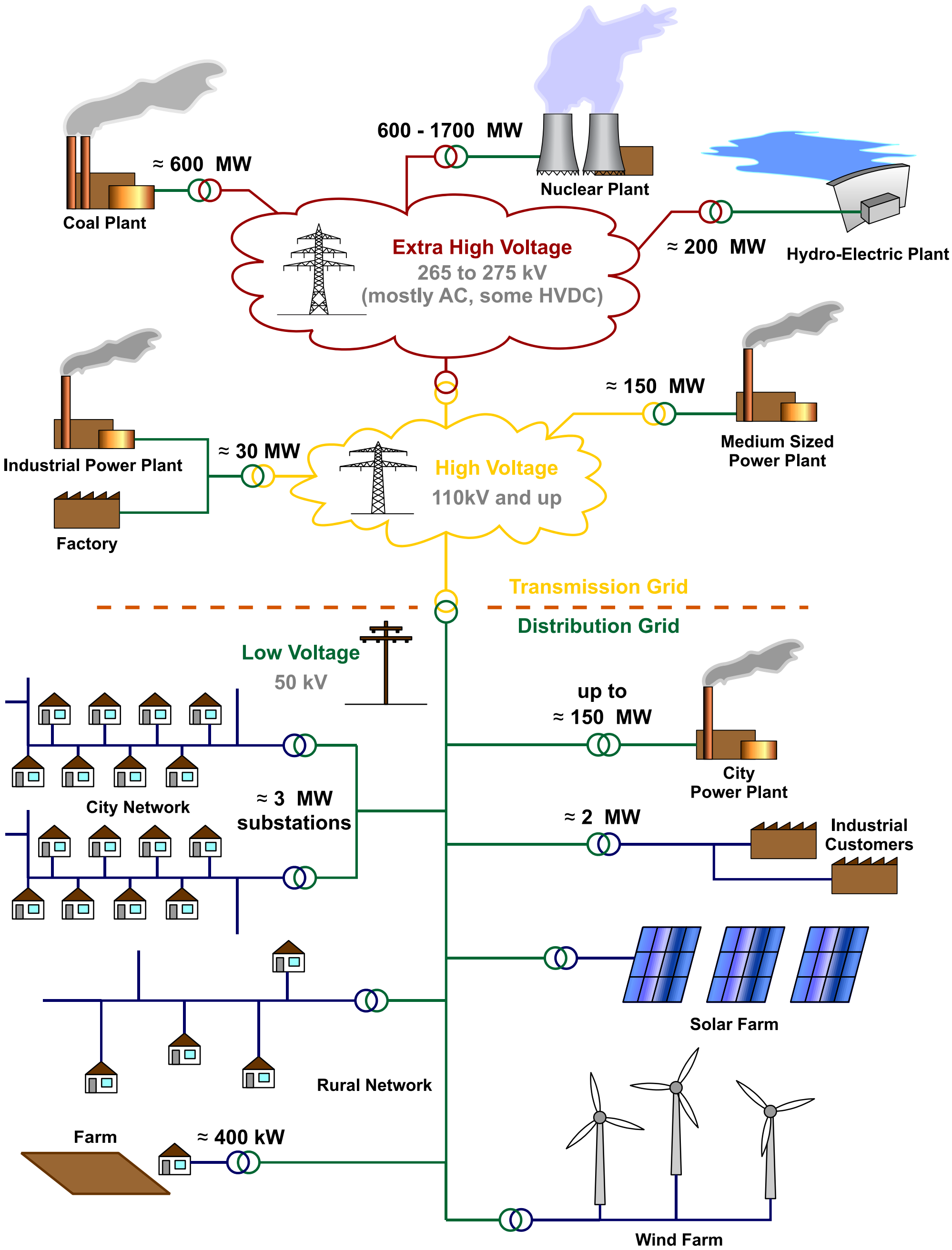

Fig. 2.2 General layout of the electricity networks in the USA [ele].

2.1.2.1 Centralised generation

It all began in 20th century when power grids started as local grids, grew over time and became interconnected for economic and reliability reasons. By the 1960s the grid became very mature with vast amounts of interconnections and numerous large centralised power plants. Locations of power stations were for the most part chosen with care. Usually they were built close to fuel supply (oil, natural gas, etc.) and cooling sources (lake, sea, river or other water reservoir).

As the grid became increasingly interconnected, a proper metering system was needed per user basis to allow tracking power consumption as it varies for each consumer. As electricity could not be easily stored without energy conversion, it should be generated at the time of demand. Peak periods highly increase the price of electricity as very expensive boost turbines need to be fired during those periods. A double tariff metering was implemented to encourage users to consume electricity during off-peak periods. This was a move towards Smart Grid metering except that technological limitations did not allow real-time pricing. This concept is expected to be fully implemented using Smart Grid technology.

Power is generated at power stations. These are industrial facilities where electricity takes its form from other types of energy. At the heart of nearly all power stations lies a generator, which converts mechanical power to electric power by creating motion between magnetic field and a conductor. There are many types of power stations. The classical ones could be classified by fuel type.

Classification by Fuel:

- Fossil-fuel power stations.
- Nuclear power stations.
- Hydro power stations.
- Wind power stations.
- Biomass-fuelled power stations.
- Solar thermal power stations.
- Photovoltaic power stations.
- Geothermal power stations.
- Exhaust gas.
- Waste heat from industrial processes.

Although the renewable energy generation has recently increased, the majority of electric power is still produced using fossil fuels (refer to Figure 2.3). This centralised power generation model is old fashioned, has high environmental impact so other solutions are currently under research. Smart grid would have a huge role in decentralising power generation and introducing renewable energy connected to the distribution part of the network.

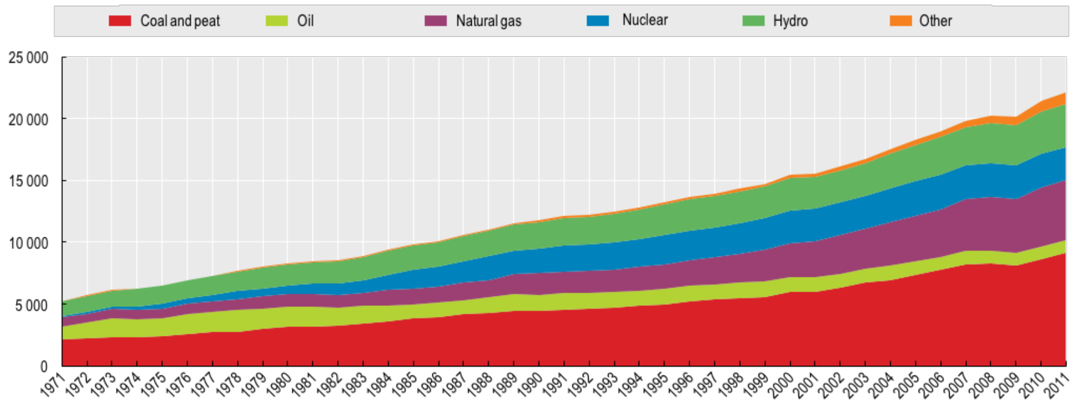

Fig. 2.3 World electricity generation by source of energy (TWh) [OEC14]

2.1.2.2 Renewables and decentralised energy

Renewable energy is usually defined as energy that originates from sources which can fully recover in a human timescale. Mostly renewable electrical energy comes from wind power, solar power, hydropower, geothermal, bio-energy and heat pumps.

Recent concerns on climate change made people look into renewable energy sources more often, that can reduce the dependency on fossil-fuels. Governments and policy makers incentivise renewable energy generation, thus there is an increase of investment in large scale green power plants as well as residential small scale renewables [Com12]. As more and more small scale power plants are installed, the grid transforms from centralised to a distributed fashion.

A large increase in wind energy has been seen during the past decade. This type of energy is captured on site using wind turbines, and can be very cost-effective in areas with adequate wind resources. Air movement is caused by differential solar irradiation and it has been estimated that there is about 10 TW continuously available wind power in the earth [HISR07]. It is about four times the global power demand, which is about 2.5 TW [OEC14]. There are many types and sizes of wind turbines, including both vertical and horizontal axis designs. Maximum power output can be as high as 8 MW and the efficiency of commercial turbines are about 75% to 80% of the Betz's limit.

Solar energy is also pushing its way to the market. The sunlight provides an abundant source of renewable energy. This technology takes advantage of the sun's energy using three main types power capture mechanisms: photovoltaic panels (PV), solar power concentration and thermal heating. Photovoltaic devices generate electricity directly from sunlight using semiconductor materials. With the help on inverters, the energy can be fed to the grid. Another popular way to generate electricity from sun is using reflective surfaces. These solar power plants use mirrors to concentrate solar energy that can drive conventional steam turbines and thus generate electricity.

Decentralised Energy (DE) is defined as energy generated at or near point of use. Smart Grid technology states that energy should be generated in decentralised fashion. More and more private rooftop photovoltaic solar panels and wind turbines are now emerging. Also geothermal, wave, tidal and small-scale hydroelectric power have also become more popular. Micro Combined Heat and Power (CHP) could contribute in electricity generation at residential houses as well. And for all this electricity to be controlled there is a need for a mechanism, which would sense, track and route electricity in an intelligent and efficient way.

There is a large economic motivation for decentralised generation. Depending on the market, the network price component is about half the total price that the end user pays per kWh. By adapting decentralised micro power stations, the generation is moved closer to the customer thus decreasing the transmission and distribution costs. On the other hand, DE have other problems associated to it such as energy balancing and power management.

2.1.3 Electric energy balance using storage

Unfortunately, electricity is the most perishable commodity in the world. It cannot be easily stored in its form and must therefore be used at the same instant as it is generated.

The most known method of storing electrical energy is using batteries, but in fact, this requires energy conversion from electrical to chemical energy so it should not be considered as direct electrical energy storage method. There are numerous types of electrochemical batteries, but mostly flow batteries are recognised for grid usage due to several advantageous properties [WMM$^+$11]. More detailed information on these batteries can be found in Section 6.2.2.

Electricity can also be converted into heat in district heating plants. This is done by using heat pumps and electric boilers, which function as big immersion heaters in enormous hot water tanks. In this way the surplus of electricity can be stored as hot water that can be used when needed for heating our houses. In a similar way, every individual home can store energy in hot water tanks when there is a surplus of electricity or when the price is low. This fact is wery important since major part of this thesis analyses the possibility of such energy storage technology be adapted to benefit electrical energy balancing and renewable power integration.

Pump-storage hydroelectric facilities also provide electricity storage for load balancing. They can be used for economic reasons - store energy when the price is low and sell when it is high. The energy is stored by pumping the water to higher elevation thus storing gravitational energy and *vice versa*. The typical cycle efficiency is from 70% to 85% [LoCaBT07].

In the future, when the number of electric vehicles increases, electric vehicles will be charged and used as electricity storage. One car does not make a difference, but when thousands and possibly millions of them are combined, it is a noticeable storage capacity. So whenever an electric car is not used, it could serve as storage to balance out electricity generation and consumption mismatch.

Superconducting magnetic energy storage systems or super capacitors might also be used to store surplus of electricity in the near future. Also compressed gass storage, flywheels, hot rocks and other technologies exist in the literature but main focus in this thesis is on flow batteries and hot water storage. Given all these possible storage technologies every house will not only be consumer of the electricity, but also producers. Every house will become what is known as 'prosumer' of energy.

2.1.4 Smart grid technologies

The current electrical grid is out-dated and needs to be upgraded. The revolution in communication systems (mainly internet) offers us the possibility of monitoring the grid and interconnected units in real-time. The European Technology Platform [Com06b] defines smart grid as *electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies.*

The vision of implementing a Smart Grid has a lot to promise. It is believed to be the only way to de-carbonise our power sector at a reasonable cost [EJL$^+$12]. There are many other reasons why Smart Grid should be implemented now. Just as internet revolutionise the way we communicate, Smart Grid roll out will revolutionise our everyday life and the way we consume energy. It will improve the prediction of generation and consumption, allow the use of energy in more efficient fashion, and provide safety, robustness and resilience.

In many parts of the world current transmission and distribution networks are beyond its designed life, thus needs replacement. It is a great chance to implement Smart Grid technologies instead of rebuilding the old fashioned grid. With the increase of distributed power generation plants (small and medium size solar, wind and hydro power plants) it is a necessity to track power flows and monitor the capacity of transmission lines. Recent development in communication industry allows Smart Grid to be easily deployed. Most of the houses in the developed world already have internet connection so it is only a matter of installing smart devices. In fact UK has planned to change all electricity meters to smart meters by 2020 [hou12].

Smart Grid is an emerging technology. It combines communication and power electronics layers along with many other components. It is mainly referred to a set of technologies that enhance the use of traditional power grid. It introduces many features that were not possible before 21st century including computer-based sensing, monitoring, remote control and automation. Many countries around the world invest millions of pounds in research and development of this technology. Some of them already started implementing it in real-life to test and prove the concept.

In terms of the improvements of the continuity of energy supply, Smart Grid would improve power quality and minimise power outages as well as blackouts. The vision is to be able to predict power line damage before it even happens. In case of disrupted transmission lines, Smart Grid would be able to self heal by re-routing the power flow using alternative or redundant route. In this thesis the focus will be brought on managing, controlling and balancing the intermittent renewable energy generation, connecting the smart devices to the grid, using techniques such as Demand Side Management (DSM), Demand Response (DR), Real-Time Pricing (RTP), energy storage and forecasting.

2.1.5 Forecasting techniques and machine learning

Forecasting is becoming a growing concern in the modelling of Smart Grid systems, and the ability of agents to produce forecasts of their own behaviour, or forecasts on behalf of other agents must be addressed. Optimisation problems frequently require a forecast of the future expectations of load and resource availability given the current conditions. A couple of forecasting techniques are presented in this section.

2.1.5.1 Artificial neural networks

Artificial Neural Networks or ANN for short, or simply ‘neural nets’, are a crude computational tool based on the brain’s neural structure. Neural nets are inspired by the sophisticated functionality of the human brain as well as those of other biological organisms. They are used to estimate functions whose outcome is reliant on very many different inputs. Neural Networks are the artificial equivalent of naturally occurring Biological Neural Networks (BNN), and both network systems are constructed from neurons. However, ANNs are very different from BNNs, where the former is constructed based on the characteristics and concepts of the biological systems. A neural network is made up of an input layer of neurons, one to three hidden layers of neurons, and another layer of output neurons [Kwo11].

These ANNs have the ability to 'learn' and discern patterns from the information that flows through it. Data flows through the ANN when it is being trained and during its normal operation. A typical neural network can have between 10 to millions of artificial neurons (units) in a series of layers. It is also important to note that once a neural network has been trained, it can start to produce independent results [Kwo11]. Data is fed through the input units; this triggers the hidden units in the second layer which eventually arrive at the output units. Figure 2.4 depicts the general layout of an ANN.

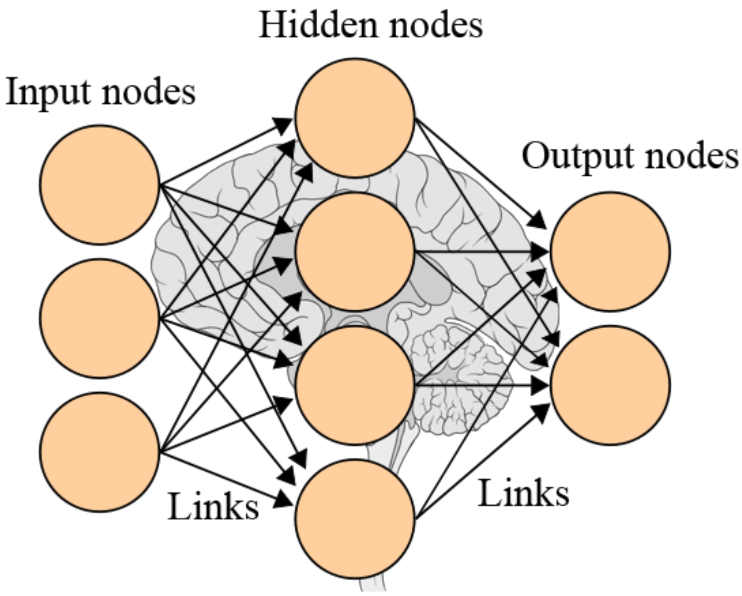

Fig. 2.4 The general layout of an ANN.

Neural network training requires a large amount of historical data. In fact, the more data there is, the better neural network can be trained. The data is split into three datasets - training, validation and test. The training dataset is used to fit or train the ANN, while the validation dataset is used to monitor and decide when to stop the training process. The performance of the ANN on training dataset should always increase during iterations (epochs) as the neural network is altered to fit the historical data better during every training cycle. On the other hand, the performance of the same ANN on the validation dataset should start to decrease once the ANN starts to get overtrained, thus the best performing epoch is the one which produces best performance on the validation dataset. Finally, the test dataset is used to evaluate unbiased performance of newly trained ANN.

Neural networks are suited for numerous tasks, especially when no functional algorithm for the task exists. This biologically inspired computing method also provides a smoother degradation in case of a system overload, as opposed to the more conventional alternatives. The ANN can be 'trained' to accomplish this using sample data and a feasible teaching method. It is important to note that identical ANNs can eventually perform different tasks depending on the 'training' method used. In essence, the ANN can be regarded as an expert in that information category that it has been trained to analyse. The importance of ANNs stems from their remarkable ability to derive patterns and meaning from very complex data sets, especially patterns that have been interfered with noise [SJ06].

In this project, the ANNs were used to predict real-time pricing for Demand Side Management (DSM). Among other modelling techniques, they were also used to forecast thermal energy use, in particular, hot water consumption at residential houses. Demand side management of the electricity grid notifies consumers to lower their consumption as opposed to adding more generation to the system when there is a rise in system demand. Consumers are often given an incentive to participate in DSM through a real-time pricing mechanism. A Demand Response (DR) is the resultant alteration of consumer electric usage patterns in response to a shift in price or because of other incentives. In this regard, the ANNs were used to predict how consumers will react to certain DR events given a certain price of electricity. The ANNs were chosen as one of the forecasting methods because they are very flexible and robust in terms of the data that they can handle. They require little formal statistical training, they have the ability to implicitly detect complex nonlinear relationships between dependent and independent variables, and the ability to detect all possible interactions between predictor variables. A single ANN topology can be designed that works for many different users and learns the pattern of a particular consumption unit (dwelling). The neural network would identify patterns in the load profile that would have otherwise been impossible through other conventional methods [Kwo11].

In order to forecast thermal energy use at residential homes the ANNs were embedded inside a smart water heater. The water heater is a very flexible energy consumer in the household, and it was selected as the ideal device to use and study the energy shifting capabilities in residential homes. The neural network analysed the data on volumetric hot water usage in residential homes to predict future usage patterns. It is important to note that water usage also follows a resilient and repetitive pattern. First of all, most of the water is used by people thus there is an inverse relationship between sleeping times and water usage. There are also distinctive morning and evening peaks of water demand during weekdays. Most daily patterns look similar except for weekends when people most likely behave irregularly.

2.1.5.2 Seasonal autoregressive integrated moving average

Another example for modelling and forecasting data is Box-Jenkins methodology [BJRL15]. Since time-series data (periodic measurements of particular important variable) is extremely common, there are many variations and implementations of previously mentioned method that works well for different types of time-series. The particular model depends on stationarity, nature of the process, resolution and also accuracy that is required. The purpose of time-series analysis is to find and understand the relationship between data and exploit them by forecasting future values.

It should be obvious that good forecasting results require comprehensive understanding of time-series' properties and their nature. Exploratory analysis of time-series involving visualisation plots, decomposition into deterministic and stochastic parts, and studying the dependency structure is the key to successful forecasts. Time-series often demonstrate trends, seasonal effects, random cyclic variations and autocorrelations. Without thorough investigation, one time-series might look highly periodic and exhibit seasonality, when in fact a very regularly looking periodicity could be caused by stochastic variation. This leads to the important concept of stationarity.

It is very important to understand how stationary the time-series is. In general, stationarity means that the probabilistic properties of time-series must not change over time, this means any section of series exhibits the same statistical properties for every other section with the same length. If this is not the case then the series should not be considered as stationary and either spatial models applied or further transformations performed on the data.

In practice, the data almost never looks exactly the same for different periods from a statistical point of view, i.e strictly stationary. A weak stationarity is the *de facto* boundry between stationary and non stationary data. Fortunately, weak stationarity is sufficient for applied time-series analysis. There are many practical ways to determine time-series stationarity, for example Augmented Dickey-Fuller test, Philips-Perron test, Kwiatkowski–Phillips–Schmidt–Shin test, Leybourne-McCab test, Elliott-Rothenberg-Stock test, Canova-Hansen test, etc [GG15b].

One of the main tools for making time-series stationary is differencing. This technique does not remove information and can be applied recursively to achieve higher orders of differentiation. It should be mentioned that both simple differencing (when the difference is calculated using two consecutive values) and seasonal differencing is available for removing trends and seasonalities. Other techniques include deflation or logging [TT02]. Another way to decompose time-series into trend, seasonal and remainder parts is using simple running means (for trends) and average patterns (for seasons). On the other hand, using running mean is not the best way to smooth the data thus locally weighted scatterplot smoothing (LOESS) is used.

The autoregressive moving average (ARMA) processes show great importance in modelling real-world data. It is strictly used to fit stationary data and comprises of a combination of autoregressive model and moving average model, both of which often complement each other. A modification of ARMA is ARIMA, which includes integral term, i.e. removes the deterministic trend by differencing. According to Gerolimetto [Ger10], most economic time-series are non-stationary, thus ARIMA becomes very useful. The integral part has order parameter so different non-stationarity orders can be removed. To model seasonal time-series, another derivation of models is used - seasonal ARIMA or SARIMA. It is also sometimes being referred to as multiplicative ARIMA and takes a form of ARIMA$(p,d,q)\times(P,D,Q)_S$. SARIMA model is often used for forecasting social, marketing and economic related problems. In this thesis the model uses seasonal variations and linear regression method to obtain peak load variation that occurs due to hot water usage.

2.2 Demand side management in smart grid: A review and proposals for future direction

Demand side management in smart grid: A review and proposals for future direction

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Abstract

This paper mainly focuses on demand side management and demand response, including drivers and benefits, shiftable load scheduling methods and peak shaving techniques. Demand side management techniques found in literature are overviewed and a novel electricity demand control technique using real-time pricing is proposed. Currently users have no means to change their power consumption to benefit the whole system. The proposed method consists of modern system identification and control that would enable user-side load control. This would potentially balance demand side with supply side more effectively and would also reduce peak demand and make the whole system more efficient.

2.2.1 Introduction

Even in the most developed countries electricity grid that is used today was designed more than 50 years ago and is becoming outdated. By modernising electricity grids it is possible to increase the efficiency of electricity production and the use of grid assets, to decrease carbon footprint and to make the whole power network more reliable and secure. New technologies are currently being developed that will enable so called smart grid. Although smart grid does not have a single clear definition, the European Technology Platform [Com06a] defines it as follows: “A smart grid is an electricity network that can intelligently integrate the actions of all users connected to it - generators, consumers and those that do both in order to efficiently deliver sustainable, economic and secure electricity supplies.”

The idea of a smart grid has been around for a while and recent technological advancement in communications and sensing areas enables the development of smart grid. The traditional power grid landscape consists of centralised generation, where energy is pushed one-way through transmission and distribution networks to the end users. Currently this paradigm evolves by adding distributed renewable energy generation, distributed energy storage, utility scale renewable, utility scale energy storage, etc. It is also converting from radial networks to mesh networks with the possibility to reconfigure and self-heal. On top of the existing power network layer there will be a new communications layer for information exchange and control. The whole landscape is dramatically changing from what it has been historically.

From the global perspective, main drivers behind smart grid are capacity, efficiency, reliability, sustainability and customer engagement. Higher capacity electricity grid is needed in most developing countries. At the same time electric vehicles will also demand some changes on the grid in most developed countries. Electricity throughput can be increased by enhancing efficiency. At the same time the virtual capacity would be increased using peak-shaving techniques [ZGL08]. Reliability is another big issue. Most of the system failures that lead to outages occur as a result of problems in the distribution system. Information from advanced sensors through supervisory control and data acquisition (SCADA) system might help to prevent accidents or react to the fault more rapid. Smart grid also looks at sustainability problem, where one of the major elements is the interconnection of renewable generation and how that generation is managed in order to meet the demand. Finally, residential customer engagement would enable demand side management to reduce the peak load, thus decreasing the required capacity and cost as well as increasing the overall efficiency.

Two main elements when considering efficiency are losses in the system and how the assets are deployed/used. Losses often depend on the load shape in the system, for example partially loaded transformers are less efficient, so it is desired that system operates at near capacity level. Utilisation of system is a major factor when considering investment in system assets. Optimal planning of how system assets should be deployed and used (energy management) plays a key role when considering overall system efficiency.

Smart grid technologies mainly focus on advancements in distribution side of electricity network. Many people associate smart grid term to smart meters placed at the end users. The main goal of this paper is to overview demand side management technologies focusing on demand response (DR) and user engagement techniques.

2.2.2 Demand side management (DSM)

Demand side management is the planning, implementation and monitoring of utility activities that are designed to influence customer use of electricity. As a result, it changes the time pattern and magnitude of utility's load. Usually, the main objective of demand side management is to encourage users to consume less power during peak times or to shift energy use to off-peak hours to flatten the demand curve. Sometimes instead of flattening the curve it is more desirable to follow the generation pattern. In each case, there is a need of control over customer energy use.

Reliable operation of power grid is primarily dependent on perfect balance between supply and load at each given time [KN09]. It is not an easy task to maintain balance, assuming there is very little control on the demand side (generation side can be controlled according to the load). It gets even harder when distributed energy generation increases. Renewable generation varies with weather conditions and it is not generally easy or desirable to modulate the output of renewable in order to follow a particular load shape [Str08]. Also, peaks in renewable generation do not necessarily coincide with peak in demand so energy needs to be either artificially consumed or stored for later. The system could continue to rely on fossil fuels during peaks, but due to increased variability in generation, utilities would be forced to keep bigger margins of reserve, which would dramatically increase the total cost of electricity. The alternative of maintaining the balance is to use new methods and technologies, mainly the ones that are based on user engagement. To sum up, the classical approach is to supply all the required demand whenever it occurs, but the new strategy states that the demand should be controlled by engaging users as well to respond to current state of the system.

Demand response will indeed play a key role in electricity balancing act in the future. Currently consumers have no means of receiving information that would reflect the state of the grid thus cannot react to reach the balance and increase efficiency. Due to the nature of renewable, it is not possible to control or request power when it is needed. The main objectives of DR techniques are reduction of peak load and the ability to control consumption according to generation [PD11]. In other words, there should be a way for end-use appliances to know and react when cheap renewable energy is available and when there is a shortage of electricity.

There is a significant scope for DSM to contribute in increasing the efficiency and use of system assets. Demand side management has been considered since the early 1980s. It can be used as a tool to accomplish different load shaping objectives, such as peak clipping, valley filling, load shifting, strategic conservation, strategic load growth and flexible load shape [Gel85] (Fig. 2.5). The combination of the mentioned techniques enables the load shape to follow generation as close as possible. It could decrease the amount of assets needed to fulfill current demand using existing methods of power generation (mostly fossil-fuel) and would significantly increase the load factor [Str08].

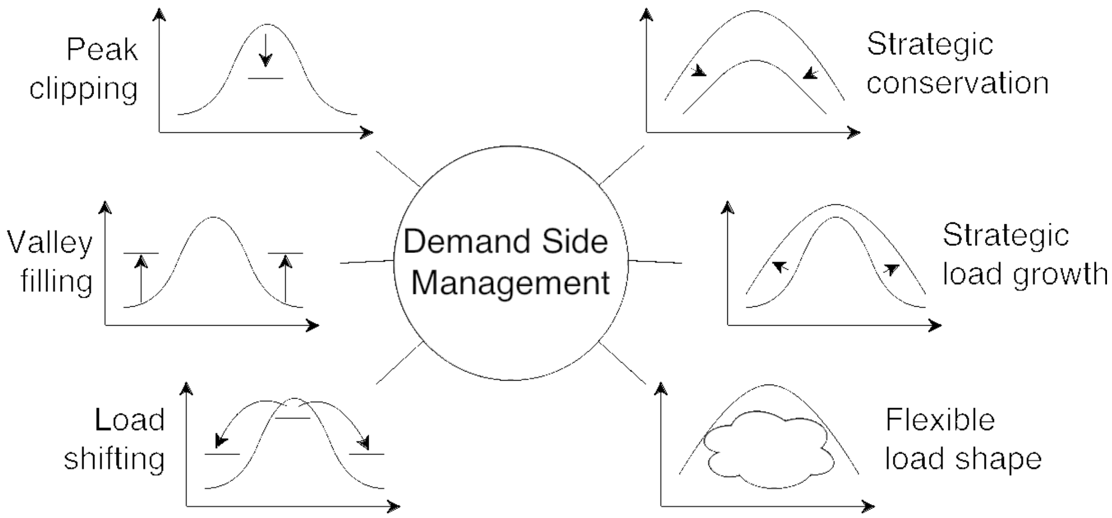
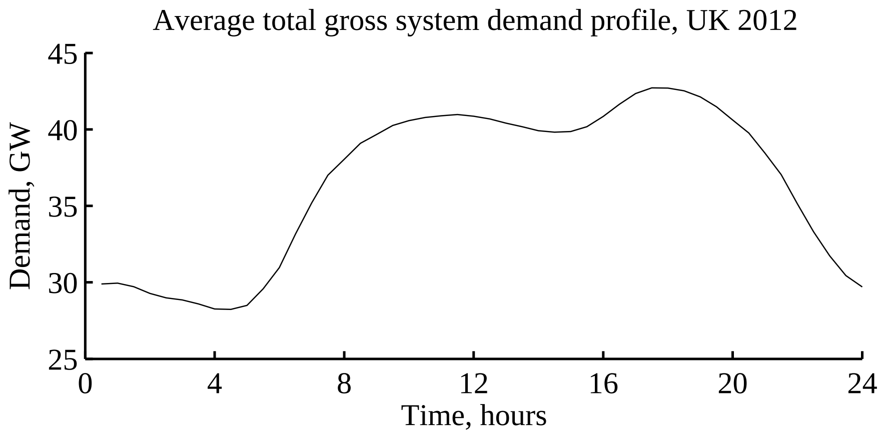


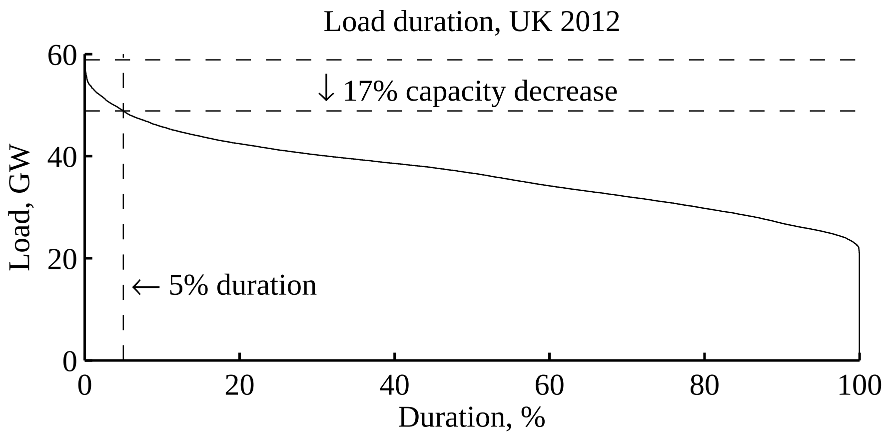
Fig. 2.5 Basic load shaping techniques [Gel85].

Utilisation of assets has the biggest influence over the price of electricity. Generation, transmission and distribution assets need to be built to meet peak demands, thus high peaks contribute to the biggest portion of electricity price. Electricity system in the UK has relatively low utilization of generation and network assets - about 50% [Str08]. Figure 2.6a shows recent average demand in the UK and Fig. 2.6b shows average load duration in the UK. It can be seen that if the demand was controlled during critical 5% of the time, there would be a huge decrease in the required asset and even more dramatic decrease in electricity generation cost.

The UK Climate Change Programme aims to decrease carbon emission. According to Climate Change Act 2008, UK has to cut 80% of carbon emissions by 2050 (compared to 1990 levels). Energy sector is a major contributor to carbon footprint. In particular, electricity system is expected to make significant contribution in decreasing pollution that is originating from fossil-fuelled power plants. The deployment of low carbon renewable



(a) Average total gross system demand.



(b) Load duration.

Fig. 2.6 System load in UK 2012.

energy generation has already been started and is expected to increase in the future. The introduced inherent variability of renewable sources could be managed by matching the demand to supply, which is where DSM might come into play.

Another driver for modernising distribution system is to be able to charge customers with real time price of electricity. The way electricity is sold now does not meet modern market principles [Sch04]. When the good is scarce, prices rise, suppliers want to sell more and consumers decrease their consumption. Due to the fact that electricity is a very short-term commodity and economically non-storable, i.e. it has to be consumed the moment it is produced, markets constantly experience short-term changes as capacity fluctuations from surplus to scarcity due to the hourly and daily fluctuation in demand. Fixed electricity tariff is simply very archaic and introduces cross-subsidies between customers. There is simply no incentive for customer to contribute in making the system more efficient [TL07]. Figure 2.7 shows how price based incentives and increased number of renewable change price elasticity. Vertical demand curve represents inability for customers to react to the real-time market price of electricity. If real-time pricing was implemented, the price would become elastic on the demand side opposed to fixed price tariff. On the other hand, increased number of renewable would also reshape the supply curve. During the times when green energy is scarce, the price for the same amount of energy would increase, shifting the curve up. That happens because renewable energy, like wind or solar, has very low running costs. All in all, demand response techniques would allow customers to participate both saving money and being more environmentally friendly.

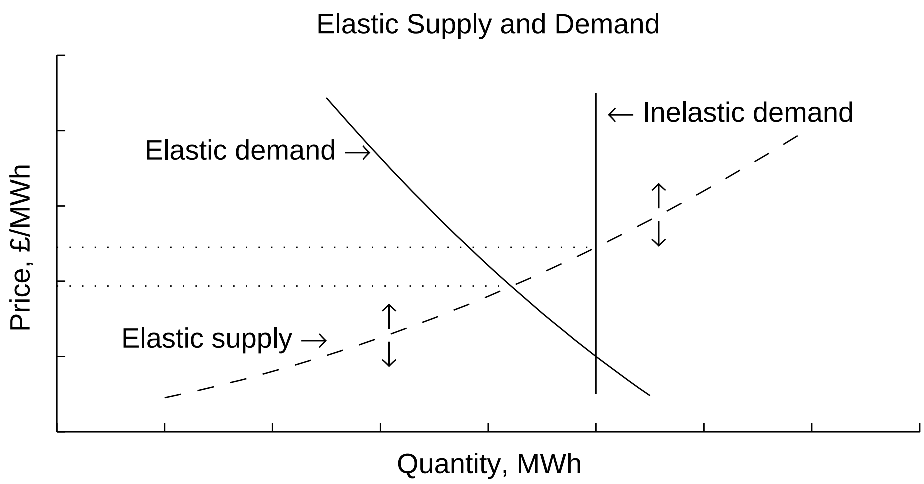


Fig. 2.7 Supply and demand of electricity.

Payback of investment in assets is another big consideration when planning system expansion. DSM would play a key role in increasing return of investment by increasing utilisation of assets and making electricity sector more attractive to investors. As the designed useful lifetime of UK electricity grid comes to an end, there should be some consideration on the strategy for infrastructure replacement and investment in new technologies.

2.2.3 Demand response (DR)

Demand response is a specific tariff or program to motivate end-use customers respond to changes in price or availability of electricity over time by changing their normal patterns of electricity use. It can also be defined as incentive payment program to reduce usage of electricity when grid reliability is jeopardised [doe06].

There are three actions a customer can take in response. Customers can reduce load only during critical peak time and maintain normal load pattern during off-peak time. This induces a decrease in customers comfort as they are forced to curtail electricity usage at certain times but reduces the overall consumption thus reducing electricity bill even further. The second action that could be taken in order to respond to high electricity prices or low availability is to offset electricity use from peak to off-peak time. This method would flatten the load shape by both decreasing the peak load and filling low consumption valleys. It does not reduce the average amount of energy used by the end users, but increases the transmission and distribution efficiency as the system operates in more stable mode. Finally, customers can use on site generation to reduce demand seen by the utility. This would increase user autonomy, further decentralise generation and decrease average load on distribution and transmission grids. On the other hand, it would maximise system complexity.

To accomplish load shaping, deferrable load appliances are needed. Ramchurn, Vytelingum, Rogers, and Jennings [RVRJ11] suggest to divide all residential loads into four groups: wet, cold, water heating and space heating. Devices from these categories behave very differently. These four device types can be further categorised as thermal loads and shiftable static loads (SSL), for example wet types should be classified as SSL because they usually run at a set period of time and consume a certain amount of energy, whereas thermal loads are more dependent on external factors such as usage and surrounding temperatures. Ramchurn et al. [RVRJ11] also state that currently penetration of electrical heating is around 7% in the population of UK and SSLs take about 20% of total energy consumption. It is also expected that electricity usage for heating increases significantly, thus giving more room for DSM to maximise efficiency.

Hardware implementation is needed for users to respond rapidly. Energy management units (EMU) can communicate with all residential smart appliances in order to coordinate their consumption. The communication from utility to end user might include various types of information. There are four control strategies that can be established between the customer and the utility - passive, active, interactive and transactive [Cha05, tee08, FSC11].

Many different DSM and DR methods are overviewed in [Str08] and [AES07] to accomplish these tasks. These methods can be divided into two main groups: incentive based programs and price based programs. Incentive based programs could be further classified as classical or market based. Using classical incentive based program the end user is involved in load shaping by agreeing to either give-up control of certain appliances (direct load control) or to react by limiting the total use of electricity (load limiter or interruptible program). Users who agree to participate but do not respond would face penalties according to the program terms and conditions. Market based programs would allow users in various incentive based load reduction programs where users could bid load reductions and Buyback electricity, participate in emergency DR, etc. [doe06]. The price-based programs (PBP) would operate using dynamic electricity pricing rates that would reflect price and availability of electricity in real time. The simplest form of PBP is time of use (TOU) and consists of peak and off-peak rates [GC93]. It is already widely implemented due to the fact that it needs least enabling technologies. In addition to TOU extreme peak pricing can be used to shave of peaks during extreme situations. The most complex (both hardware and ICT) method is real time pricing (RTP). It controls price in real time to shape end-use load. Information about implementation and experiment results of DR programs can be found in [Cha05]. Real time pricing is the most promising DR technique. It follows standard economic rules. Opposed to other incentive based programs it does not directly limit users consumption, thus users always have a choice of their load patterns. It would not raise huge policy issues, as RTP does not involve any intervention from utility side to customers promises opposed to incentive based programs.

Demand response is challenging from both technical and policy perspective. Most of the DSM techniques requires a reliable and high bandwidth connection in order to have two-way communications between users and utilities to transmit price signals, bid data, etc. Also DR is hardware intensive. Participating users would have to install home energy management units and smart appliances to be able to respond on time without human interaction. DSM and DR will benefit both users and utilities as well as make the overall system more secure and maximise social welfare.

2.2.4 Distributed energy resource (DER)

Decentralised energy resources are small, modular energy resources and storage technologies that provide electric energy where it is needed. It can range from utility-scale to residential size electricity supply. The world is gradually transitioning from large centralised power plants towards small-scale distributed generation ones. CO_2 emission reduction programs play key role in increasing distributed generation (DG) as large portion of renewable are small-scale plants. There are many incentive programs for small-scale solar power plants throughout the Europe. The buy-up price sometimes reach four times the retail price of electricity. Developing countries show high increase in distributed generation in the last 20 years.

There are many benefits of distributed generation. Firstly, it would decrease overall power flow on transmission and distribution networks, thus decrease the associated losses and assets cost. Secondly, technologies like micro-CHP make use of huge amounts of heat generated locally, which can be used for space and water heating. Finally, DER allows islanding which is an important topic when talking about reliability and security of the system. On the other hand, DER faces a lot of challenges. Renewable introduce uncertainty on the generation side, which will require increased amount of reserves. It is usually provided by the standing reserve. When part-loaded, thermal units run less efficiently, with an efficiency loss of about 10%-20%. So if unmanaged, DG will have some negative implications. Also, distributed generation power plants tend to be more expensive in terms of investment per capacity.

2.2.5 Storage technologies and electric vehicles (EV)

Electric energy is volatile. It needs to be used at the exact same time as it is generated unless converted and stored in some form. Thus it is clear that it is not possible to fully control the demand to meet uncontrollable renewable generation so energy storage is needed. To some extent, energy storage technologies decouple generation and consumption. It would help a lot in the balancing process, which is the biggest challenge in power grids.

There are many possible storage technologies in the market. According to Electric Power Research Institute (EPRI) pumped water power plants account for about 99% of the bulk storage capacity worldwide. Power output of such technology can reach up to 3 GW in a very short period of time typically 15 seconds, i.e. plants are very responsive. It is popular for high capacity, good responsiveness, high power output and high efficiency (varies between 70% and 80%). Having high capacity and fast response this technology is good for long-term electricity supply and helps increasing system stability.

Other less popular storage technologies are electric batteries, compressed air, flywheels, hydrogen, superconducting magnetic energy, thermal and liquid air. Each of these technologies have many variations with their advantages and disadvantages. Most of them can only provide short-term electricity supply due to low capacity as well as high cost per MWh. Thus storing large amounts of electricity has not yet been put to general use.

The advancement of battery storage promises an increased number in electric vehicles in the nearest future. It will increase consumption of electricity dramatically. If unmanaged, it might dramatically increase the evening peaks. On the other hand, thousands or even millions of electric vehicles might serve as huge distributed energy storage device.

2.2.6 Demand side management techniques

Loganthiran, Srinivasan, and Shun [LSS12] present demand side management strategy for load shifting based on heuristic optimisation. The proposed optimisation algorithm aims to shape the final load curve as close as possible to the desired load curve. The restriction of this strategy is compliance in the number of shiftable loads in the system, which users are willing to use at a different time. From the user point of view, this implies to a dramatic loss of comfort. Minimisation technique formulated below is used to reach the desired goal.

$$Minimise \sum_{t=1}^{N} (PLoad(t) - Objective(t))^2 \tag{2.1}$$

where Objective(t) and PLoad(t) are the desired load and actual load curves respectively. As linear and dynamic programming cannot handle large numbers of controllable devices, a heuristic evolutionary algorithm is used [LSS12]. The evolutionary algorithm achieves the best fitness for the next day, which is calculated as follows.

$$Fittness = \frac{1}{1 + \sum_{t=1}^{24} (PLoad(t) - Objective(t))^2} \tag{2.2}$$

The results of this strategy are positive and show 5%-10% operational cost reduction and 14.2%-18.3% peak demand reduction.

Similar DSM technique is proposed by [RVRJ11]. It explains a novel model for Decentralised Demand Side Management (DDSM) mechanism that allows agents to coordinate in decentralise manner. Agents control load by adapting the deferment of loads according to prices sent by the utility. The goal of the agent is to optimise the heating so as to minimise cost paid by the user. This alone can cause peaks to be shifted opposed to load shape being flattened. To overcome this problem agents re-optimise their thermal loads on any particular day with a small probability, i.e. only small portion of agents recalculate load curve at the same time. It allows total load curve to converge to optimal load factor. This technique manages to reach very high results by reducing the peaks of domestic consumers load profiles by 17% and thus reducing carbon emissions by up to 6%.

Cheng [Che12] describes the control principles, particularly agent-based control and event-based control is presented. The agent-based control enables to settle the price in auction-based market using standard economics rules. This requires consumers and generators to send their quantity vs. price bids to access the responsible party (ARP). The event-based control, on the other hand, only responds to the price that is received by the smart meter. The author also introduces virtual agents to optimise power flow in power distribution networks. Agent-based and event-based controls alone do not take into account distribution system operation parameters (maximum capacity optimal flow, efficiency). Therefore distribution system operator is given responsibility to act upon virtual agent to offset price that market settles. It takes care of constraints associated with power quality and loss minimisation. The author notes that ICT technologies introduce noticeable delay so short term fluctuations should be handled separately. Super-capacitor storage is suggested to overcome this problem. The evaluation results show that the average power flow in case of the integration of renewable energy sources and fluctuating loads can be optimised using proposed methods.

Double-auction electricity market is discussed by Fuller et al. [FSC11]. It uses transactive controllers to send bids to the central market. Price is cleared after all bids from users and generators are received. Supply and demand curves determine the actual price for upcoming period of time. Controllers adjust settings for appliances to respond to varying price after the end user receives price signal. Even though the aim of Fuller et al. [FSC11] was to demonstrate the level of details needed to perform analysis on smart grid, it proved that DR using price signals give positive results.

There are some drawbacks of using double-auction and heating, ventilation and air conditioning (HVAC) control method. First of all, bids received from users and generators are not reliable. It is impossible for renewable generators to predict their output with high certainty. There could also be fake bids from the user side that would distort price cleared by the market. It would induce reasonably big challenges for policy makers. Another drawback is the high communications requirement. There might be situations where user would like to submit a set of price/amount bids. Communication technologies would be challenged to transmit the increased amounts of data and largely increase the overall complexity of the system. Finally, a rebound of energy use after high price signal is a big issue. It could lead to even bigger peaks thus creating another vulnerability problem.

2.2.7 Proposed DSM strategy and method

The proposed demand side management strategy is based on advanced control theory. It involves system identification and model design to achieve the desired load. Figure 2.8 shows block diagram of the proposed system created using MATLAB Simulink.

The block diagram consists of four major subsystems namely generation, weather and time information, controller and the system (also referred as the plant). Each of these parts plays a distinguished role that is explained in the following section.

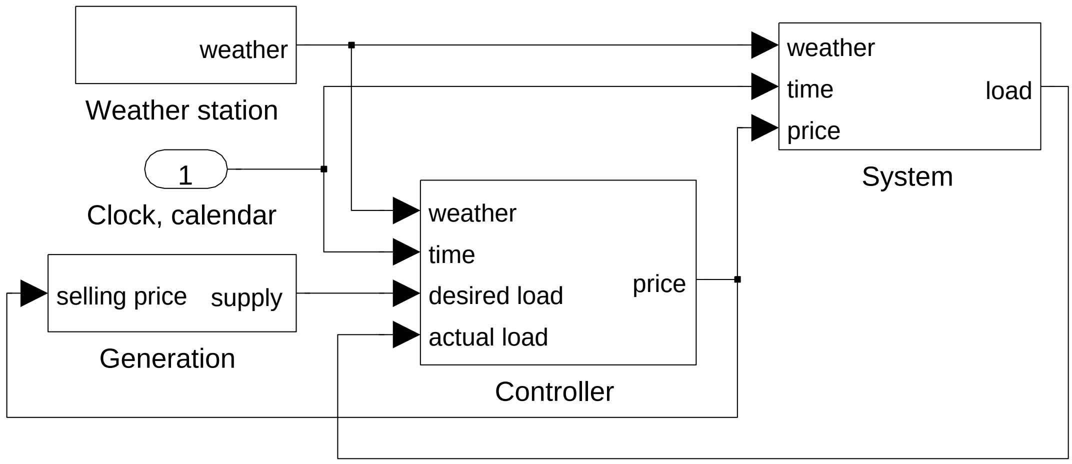


Fig. 2.8 System block diagram.

2.2.7.1 System (plant)

This control problem was approached by designing a system model that represents the electricity use behaviour of the population relevant to price level. To predict user response to price changes, GridLab-D simulation software was used. Simulations have been carried to collect statistical information and evaluate the feasibility of DR (see Section 2.2.8). Representation of population behaviour (system) was assumed to be accurate enough for the purpose of the proposed model to respond similarly in a real world situation.

The diagram in Fig. 2.9 represents the proposed architecture for modeling the system. It includes price, weather and time information as inputs. The output is the predicted demand. The size and number of hidden layers might be adjusted dependent on how well the neural network is trained for a particular area.

System identification step needs to be repeated over time for the model to adapt to the changes in distribution side of the network. It is important to have a model that is as accurate as possible in order to avoid creation of even higher peaks in demand.

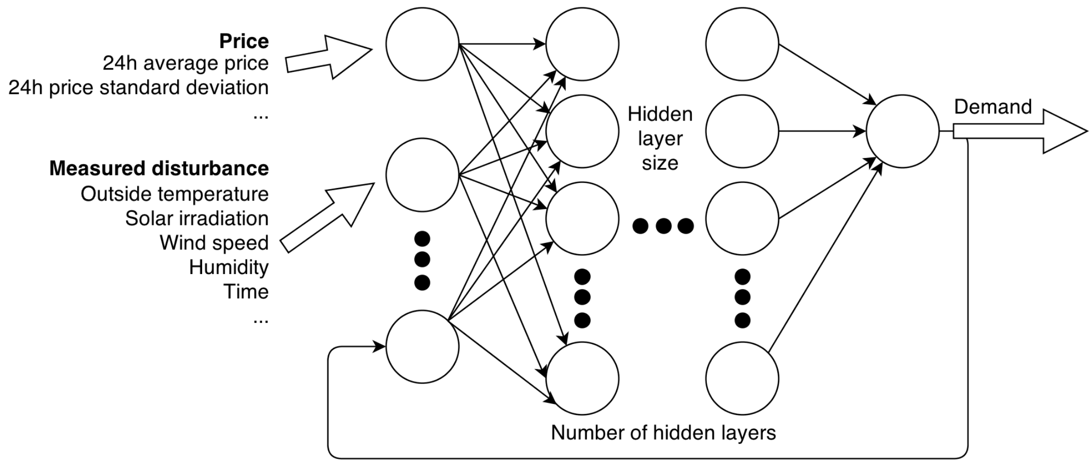


Fig. 2.9 Neural network model of the system.

2.2.7.2 Generation

Generation side supplies information about the desired load. It is the sum of all generator outputs that are currently connected to the grid. Generators connect and disconnect from the grid depending on the real-time tariff which is calculated using the feedback real-time price from the controller. When the price increases, more generators connect to the grid to sell electricity but on the other side customers shed their loads due to high price. Thus a balance is settled between generation and consumption where both ends actively participate in this process.

2.2.7.3 Weather and time information

System behaviour (consumption of electricity) is dependent on many external factors. Most important ones for HVAC is weather. Weather can be described as a combination of temperature, humidity, wind speed, solar irradiation and other measurements. This information is fed to the controller where it is processed and appropriate price signal is computed.

2.2.7.4 Controller

A controller is designed to control the price signal. The concept design of the controller is based on neural network predictive control. Figure 2.10 shows a block diagram and basic principles of operation. The controller optimises future price signal for the modeled demand to match the desired generation. Next time step only the first control input is used and the process repeats. Its major task is to compute the right price for the total load to become as close as possible to the desired load from the generation side. Model predictive control (MPC) is suitable for this application because inputs are constrained, disturbances are measured (not shown in the diagram) and time constants are large enough for MPC to perform calculations.

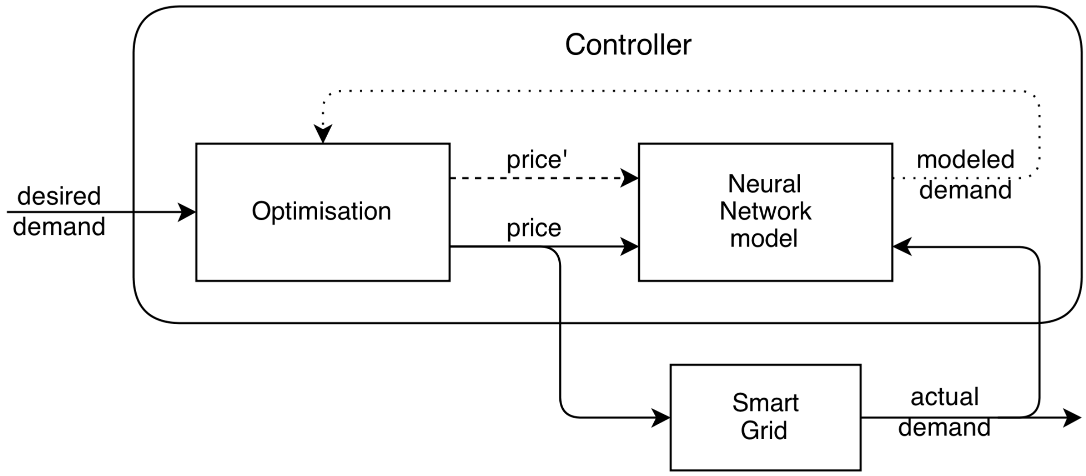


Fig. 2.10 Neural network predictive controller.

The actual load will respond to price fluctuations. Controller is tuned so that actual load matches the generation pattern as close as possible. In order to demonstrate positive results using this technique, users need to be equipped with residential energy management units (EMUs) that respond to control input (price signal). This technology would enable customers to immediately respond to price fluctuations by adjusting temperature set point as described by Fuller et al. [FSC11].

2.2.8 Demand response simulation results

2.2.8.1 Simplified one house simulation

In the first case, the simulations were simplified to a single house and only the price signal was fluctuating. Figure 2.11 shows the results of single residential HVAC load response to price change including temperature information. The outside temperature was set to a constant 10 °C and other values of the climate object were set to default. Attributes like HVAC comfortability settings, default temperature set point, house size, window to wall ratio, etc. define the transient and steady state responses to change in price signal. In particular, the interest is focused on how the total HVAC demand is related to change in price. A series of simulations were completed to collect data.

As it can be seen from the graph, price change directly influence heater operation. HVAC controller adjusts the temperature set point whenever the price changes. When the price increases, the HVAC controller lowers the indoor temperature set point according

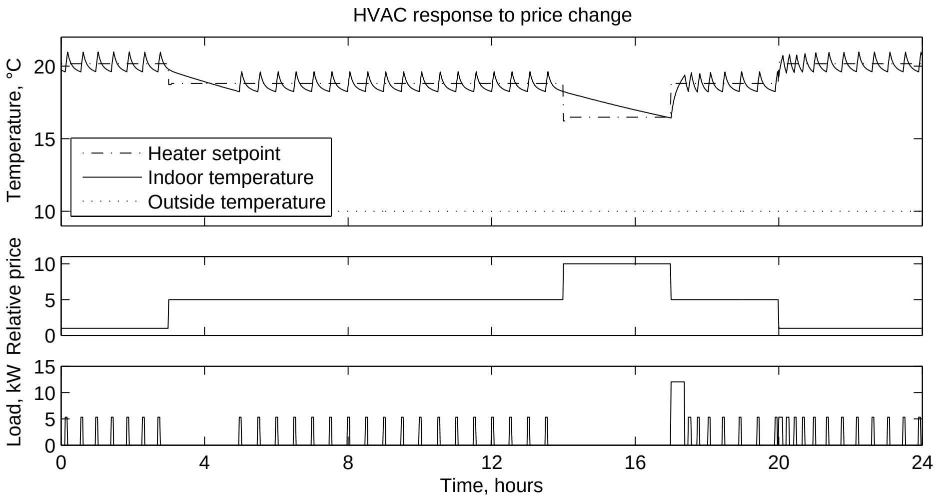


Fig. 2.11 Simulation of HVAC response to price change.

to the comfortability setting [FSC11]. This results to heater shut-off until the house cools down to the new set point. After that the steady state resumes. A different transient response occurs when price decreases. When that happens, the HVAC controller increases the indoor temperature set point due to low price, thus turning on the heater to full power to raise the temperature to a new set point.

2.2.8.2 Demand response simulation of a population

In the second case, a population of 629 houses was simulated using the standard dataset from the GridLab-D simulator [CTM$^+$]. The purpose of this simulation was to ascertain the possibility of controlling HVAC and water heater loads of a group of residential houses using price signal.

Each house was equipped with either a gas heater, a heat pump or a resistive electric heater. The penetration level of each type was set to 135 (22%), 235 (37%) and 259 (41%) respectively. High level of electric heaters was intentionally chosen to emphasise future dependency on green energy. The average floor area was 195 m^2 with a standard deviation of 27 m^2.

A passive controllers that react to real-time price were used to control air heating, cooling and water heaters. HVAC controller was used in ramp mode and settings that describe comfort level were set to same value for every house [FSC11]. In particular lower and upper offset from desired heating temperature limits were set to -1.389 °C and 0.833 °C respectively. Controllers' lower and upper ramp gradients were 0.8 and 1.33. Cooling controllers' absolute values were the same, except signs were adjusted.

Typical meteorological year for Seattle (Washington, USA) was used for weather information input. The average outside temperature from the 2nd to the 5th of January was recorded to be 7.6 °C with a standard deviation of 8.4 °C. Figure 2.13 shows outside temperature graph.

Mainly three end consumer appliance groups were used - HVACs, water heaters and other electronic devices such as lights that were modeled as ZIP loads. Table 2.1 shows statistics for each group - average load, average load with DR, mean absolute error (MAE) and modified mean absolute percentage error (MAPE). The modification of MAPE was done because of division by zero at some time steps. Equation 2.3 was used to calculate modified MAPE. Figure 2.12 shows time series load profiles for HVACs and water heaters respectively. A base consumption schedules were used for each of the groups. Other non-responsive loads are out of the area of interest.

Table 2.1 Average load by appliance group.

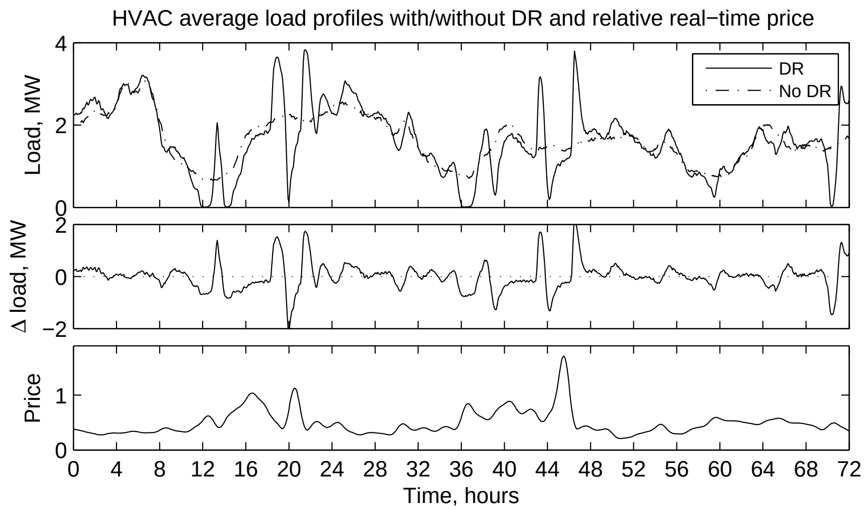
	Average load, kW (%)	**Average load with DR, kW (%)**	**MAE, kW (MAPE, %)**
HVACs	1639 (70%)	1641 (70%)	341 (21%)
Water heaters	257 (11%)	254 (11%)	23 (9%)
Other	488 (19%)	488 (19%)	0 (0%)
Total	2342	2341	349 (15%)

$$MAPE = \frac{MAE}{\overline{load}} \times 100\% \tag{2.3}$$

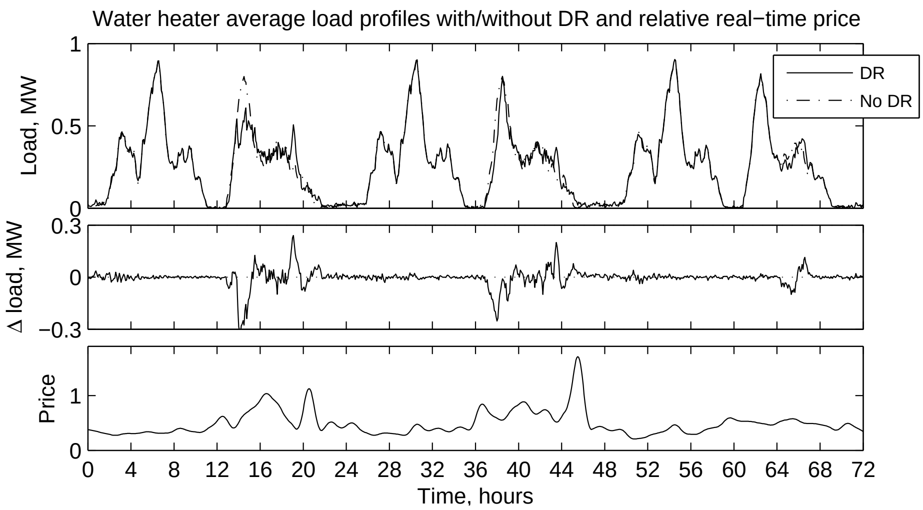
As we can see from Table 2.1, the average load maintained at a very similar level with and without DR. This also means that the consumed energy also did not change. On the other hand, high MAE and MAPE values shows that load profiles with DR are significantly different from those without DR. It proves that by fluctuating real-time price in a scenario that is described in this section it is possible to shift about 21% of HVACs' load and 9% of waterheaters' load.

It should be noted that real-time price was chosen with no control strategy (Fig. 2.12). It was based on heuristics to mime a possible price of electricity during certain periods of the day. Also, some dramatic price jumps were included to imitate extreme scenarios.

Figure 2.13 shows how average inside temperature set point changed after DR was applied and the outside temperature profile. The average HVAC temperature set point before DR is shown as a dashed line and the total average is about 19.40 °C. A solid line shows the average temperature set point in 629 houses after DR was applied and the total mean value is about 19.34 °C. Also MAE is about 0.84 °C. These numbers suggest



(a) HVAC simulation data.



(b) Water heater simulation data.

Fig. 2.12 Responsive appliance load profiles (upper), change in load profiles (middle) and real-time price (lower).

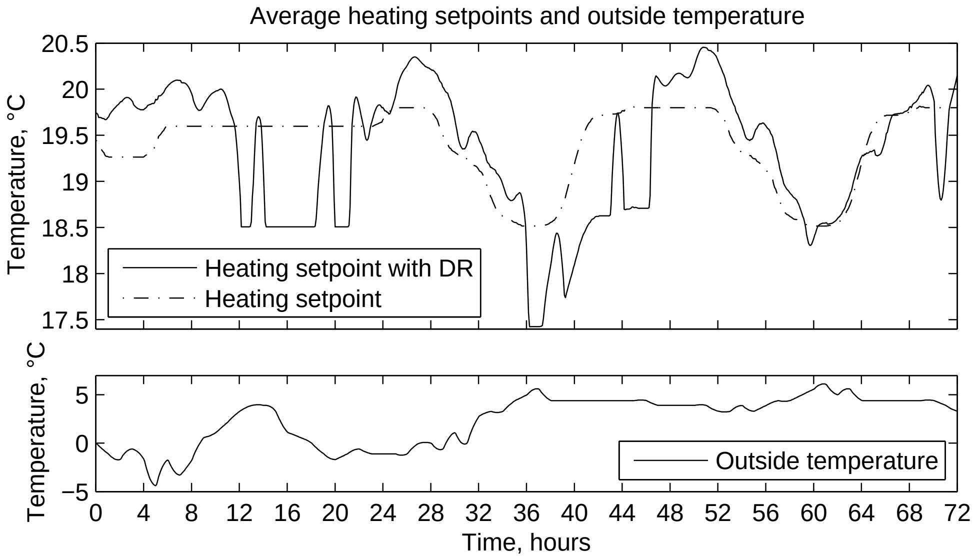


Fig. 2.13 Heating set points and outside temperature.

that the comfort was maintained at very high level because the temperature on average deviated only less than a degree and the average temperature stayed virtually the same.

2.2.9 Summary

Current electricity grid is outdated and needs a complete makeover. There are many aspects that could be improved but this paper is focused on changes at the user side - demand side management and demand response. Using existing technology and implementing new strategies it is possible to increase grid capacity, efficiency, reliability, power quality, reduce carbon footprint and increase sustainability. Demand side management ideas seen in literature and new proposed strategy was presented. All of the discussed DSM techniques are based on load shifting technique. Most of them use scheduling algorithms to optimise for objective demand profile. Loganthiran et al. [LSS12] uses heuristic optimisation to defer loads and attempt to follow desired demand. Ramchurn et al. [RVRJ11] proposes additional safety mechanism to avoid overly-homogeneous optimised consumption pattern with significant peaks. Price based incentives are used in all reviewed articles and two-way communication is necessary. Also day-ahead planning implemented in [LSS12] and [RVRJ11]. This might lead to extremely intensive communication between utility and users as every time step there is an exchange of information about the day-ahead. [FSC11] is using a double-auction market technique, which will also require exchange of load/price data pairs. Some of the proposed techniques lack short term easy to see incentives for the users. The benefits usually hide behind the social welfare. The overviewed techniques are mathematically proven, but sometimes it is too difficult to understand for everyday user. So either a less complicated technique is required or there should be more attention taken for user education to promote participation.

Loganthiran et al. [LSS12] list most popular household appliances as controllable. Shifting devices like kettles might come at a very high comfort cost. In the newly proposed technique, only highly time insensitive devices are assumed to be deferrable. HVAC system has huge thermal capacity and high inertia, which makes it a perfect candidate.

The focus of the newly proposed DSM algorithm lies on the utility side. The utility attempts to learn and model customers' response to price chance. It would then know what is the exact control input (price) to send. During normal operation, the price might reflect the wholesale price of electricity, but it can be adjusted to maintain system balance at extreme times. The proposed method is very flexible in many aspects:

- Utility does not need to know the actual control mechanism behind EMUs. User behaviour is estimated using statistical data.
- This strategy is very scalable. Different regions can be isolated and operate separately from each other.
- When divided into regions, it also gives the ability to tune controllers to better accommodate specific response, as it is very likely that different regions have particular habits or preferences of energy use.
- Customers will have the most flexibility and choice controlling their load pattern. Only customer and his willingness to pay certain price at different times define individual load shape.
- Using RTP customers are charged the real price of electricity opposed to the average price that is used now. This eliminated the cross-subsidy between users.
- A minimum amount of communication is required to send only the price information at a fixed intervals.

The biggest danger in this control problem is the creation of even higher peaks in demand at different time. The real-time price should be chosen with caution to induce the desired total demand of electricity at all times. From Fig. 2.11 it can be seen that decrease in price can create peaks in demand.

Another problem is system model mismatch. For this method to work efficiently, a very accurate representation of system model is needed. This could be done using state of the art Artificial Neural Networks.

Acknowledgment

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Chapter 3

Analysis of Real-Time pricing in Electricity Demand Response Applications

3.1 Preliminary work

The previous chapter reviewed the smart grid technologies that are found in literature. It also overviewed the demand side management and demand response techniques. Preliminary work on creating physical house models was carried out. This helped to understand the ability of HVAC devices to participate in DR. An interdependent relationship was determined between price and HVAC load and it was proposed that the use of artificial intelligence would be highly recommended. The following section discusses how artificial neural networks are used to model price and load relationship. It determines that reasonably small size ANN can perform well up to 30 minutes ahead. The work done in this chapter is used in later chapters and lays solid background in ANN usage for DSM applications and thermal load forecasting.

3.2 Neural Network Based Real-Time Pricing in Demand Side Management for Future Smart Grid

Neural Network Based Real-Time Pricing in Demand Side Management for Future Smart Grid

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Abstract

Electricity grid is currently being transformed into smart grid. Increased number of renewables require more and more ancillary services to backup intermittent power generation. A very important topic in tomorrow's electricity grid is demand side management. This tool should be used as an alternative for traditional backup power reserves. It requires a deep understanding on how consumption depends on dynamic pricing. This paper proposes a method for modelling the electricity demand response to a real-time pricing. A virtual smart house is modelled using Gridlab-D smart grid simulator. The HVAC system is setup to respond to real-time price sent by the utility. The paper is analysing the ability of neural network to predict the exact price, which is sent to the end user in order to maintain the supply balance in the system. It should also reduce the peaks in demand and increase system resilience.

3.2.1 Introduction

Supply-demand balancing act in electricity grids is a very demanding task. It requires constant monitoring of the network and very fast response to the system changes [KN09]. Poor regulation might lead to brownouts or even blackouts of the whole country. At the same time, increasing number of renewables add another layer of complexity due to their inherent variability in power output. Luckily, recent advancement in communication and sensing technologies enable the development of smart grid. It will supply utilities and grid managers with additional set of tools for maintaining system balance and stability.

A novel method is being developed at Lancaster University, which focuses on Demand Side Management (DSM) technique using Real-Time Pricing (RTP). It proposes to use machine-learning technique - Artificial Neural Networks (ANN) - to control the total consumption using pricing signal, which is sent to residential Energy Management Units (EMU). It is expected that increased number of smart appliances and intelligent Heating Ventilation and Air Conditioning (HVAC) system will contribute in reacting to the state of electricity network. The main challenge in this research is to be able to shed the load without creating even bigger peaks of energy consumption at other times.

From Fig. 3.1 it can be clearly seen that the electricity network in UK is loaded inefficiently. Figure 3.2 shows that by controlling the demand 5% of the time it is possible to reduce the required transmission and distribution assets by 17% [GG14].

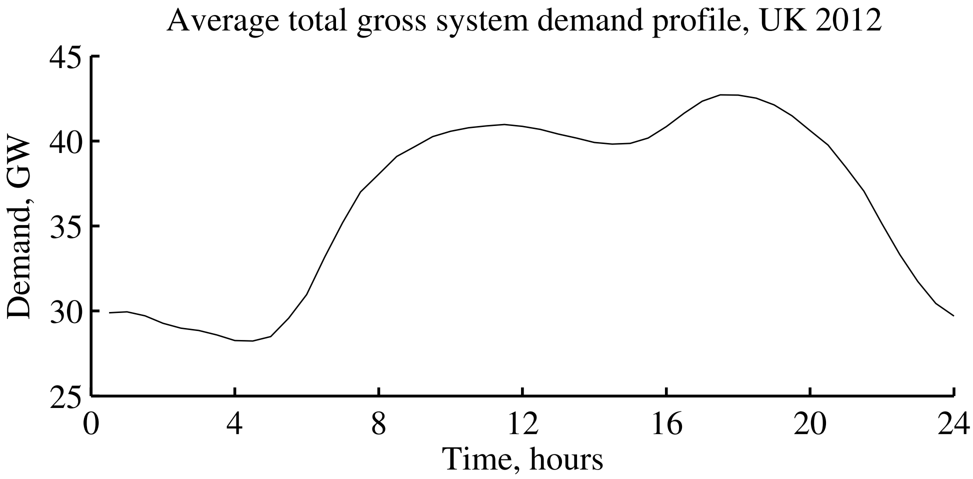

Fig. 3.1 Average total gross system demand profile in UK [GG14].

Renewable energy sources are usually intermittent, thus require power backup. Traditional power backup like spinning reserves are costly and inefficient. As a result, demand response will truly play a key role in future electricity balancing act [AES07]. It is also important to note that currently there is no way for end-user appliances to respond to excess generation of renewable energy or shortage of electricity. Enabling users to

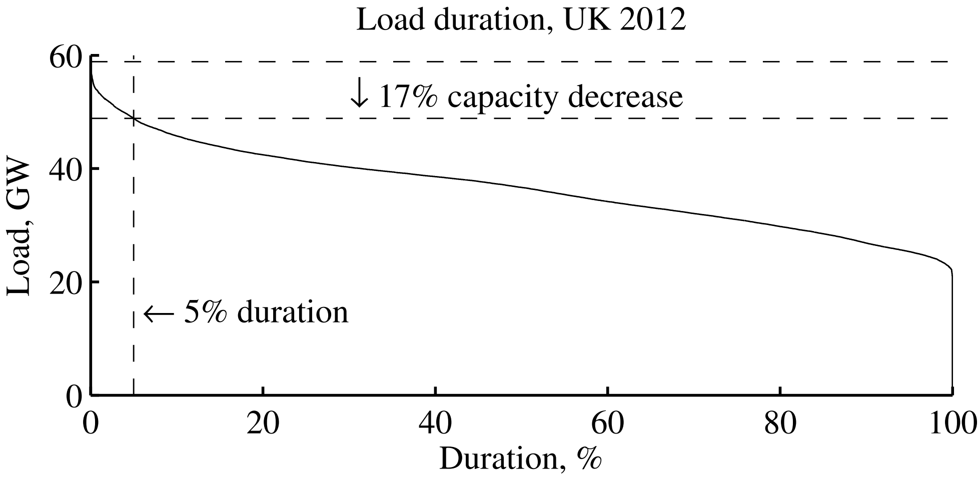

Fig. 3.2 Load duration in UK 2012.

participate in system balance will potentially increase the overall system reliability and efficiency. Figure 3.3 shows how real-time pricing would make the demand elastic [GG14], [CS12].

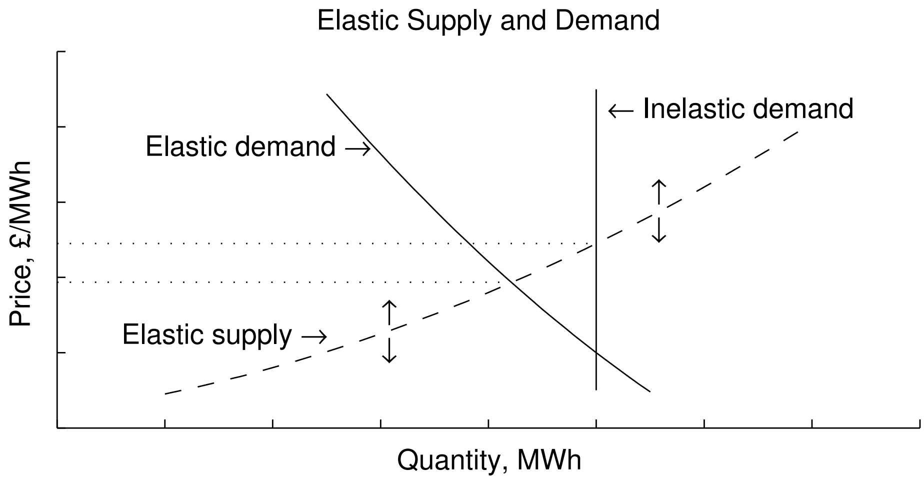

Fig. 3.3 Supply and demand elasticity.

Although the concept of Demand Response (DR) might be straight forward, the implementation is quite complex. First of all, there might be several types of incentives for the users to participate. Secondly, there must be a way of predicting the response by the user to a certain signal or event (for example price change). Also, utilities and system operators must be cautious not to create high peaks in demand i.e. a rebound of electricity usage is very common after a high-price period [PD11].

This paper focuses on electricity demand management using artificial neural networks. It proposes that it is possible to find a highly non-linear relationship between real-time price and electricity consumption (Fig. 3.4). By creating this model it will be possible to predict user response to a certain DR event. In general, load profile is highly repetitive. In addition, human behaviour tends to form habits. These are two key points that help artificial intelligence (AI) learn from past experience and predict future consumption [Yeg09].

This method stands out from conventional load profile forecasting because it predicts transient response of electricity consumption to price change. In this paper authors model a virtual house and simulate its electricity demand response to price change. This data is the used to train neural network. Hence, it is possible to forecast a new price to be sent to the EMUs for a desired demand to be reached i.e. a 30 min ahead desired demand is sent to the NN, which computes the next 30 min real-time prices.

3.2.2 Gridlab-D model

Gridlab-D simulator was used to simulate the required data for further analysis. It is an open-source simulator developed at Pacific Northwest National Laboratory, USA, funded by Department of Energy. This multidisciplinary simulator combines power and control systems, building models and retail markets [CSG08]. It provides detailed information about electricity consumption at any selected node or a combination of them. It can also output many other readouts like HVAC state, current temperatures, load, etc.

A single house model with a size of 200 m^2 was modelled in Gridlab-D simulator. The house was equipped with a 5 kW resistive heater controlled by a passive HVAC controller. The controller receives a price signal from the utility and adjusts inside temperature set point accordingly. A more detailed operation of the controller is described in [FSC11]. Some of the key controller settings are as follows:

- range_low -2 °C;
- range_high 1.5 °C;
- ramp_low -4;
- ramp_high -6.

The desired base temperature was set to be 21°C. As mentioned above, the controller is allowed to add an offset to base temperature set point i.e. decrease this base set point by 2°C or increase by 1.5°C. Considering the fact that air has a relatively high thermal capacity, it is possible to shift a large amount of energy and still maintain the inside temperature in a narrow temperature band. In fact, studies show that by adjusting the temperature on average by 0.84°C it is possible to shift about 21% of energy consumed by HVAC [GG14].

Figure 4 shows how HVAC load changes depending on real-time price. Price profile is arbitrary and the values are relative because the controller operates by comparing current price with the average price and the standard deviation of a 24-hour moving window. The overall standard deviation (SD) is 0.23 and mean price is 0.49.

The bottom part of the graph in Fig 3.4 depicts the normalised energy consumption by the heater (1 corresponds to the rated power of 5 kW). As it can be seen from the graph, the relationship between price and load is quite complex so AI is used to learn this dependency from past data. More on that can be found in [GG14]. Also, Fig. 3.5 shows histograms of both price and load.

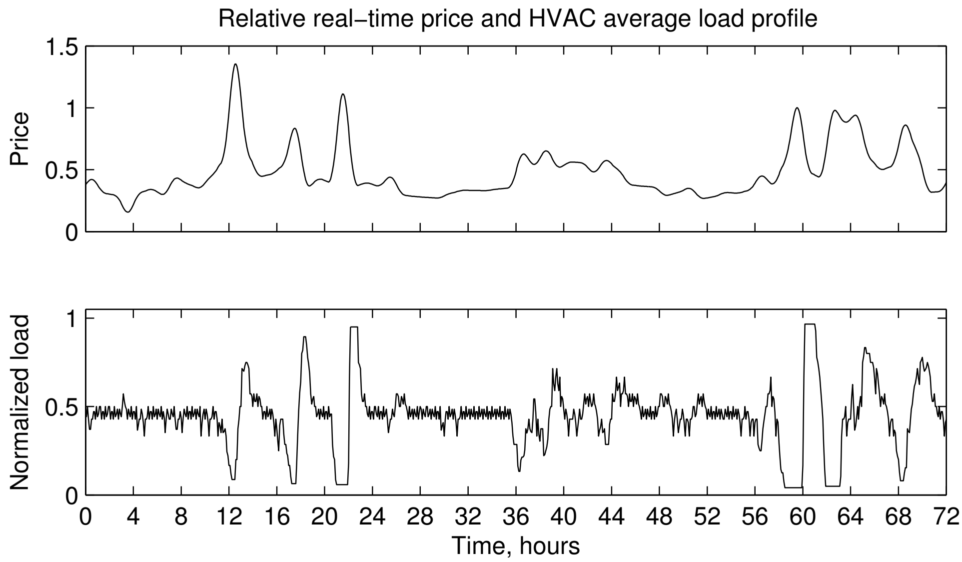

Fig. 3.4 Average load profile and relative real-time price.

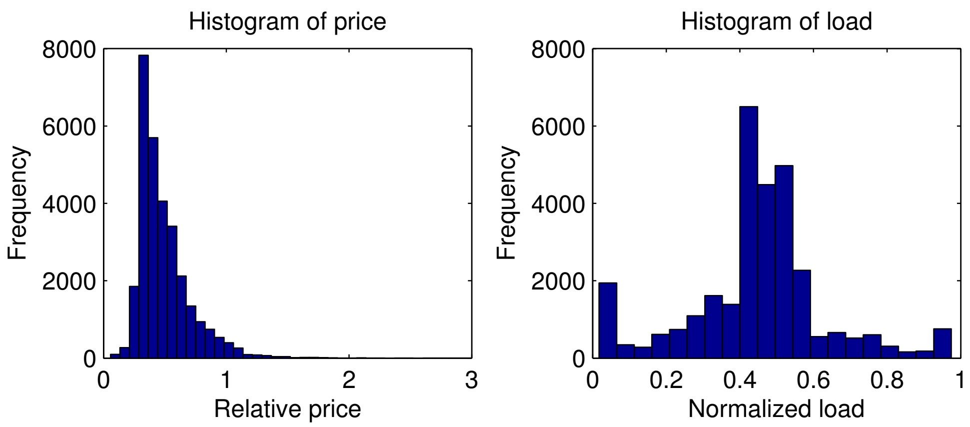

Fig. 3.5 Histograms of price and load.

As inside temperature mainly depends on the outside temperature, weather conditions are the main disturbance to the system. It should also be mentioned that these measured disturbances are currently not being taken into consideration, thus the outside temperature was set to be constant at 10°C.

3.2.3 Neural Network Model

Artificial Neural Networks are computational models inspired by human brains. Usually they are modeled as a number of interconnected neurons that compute result from inputs by feeding information through the system [Yeg09].

Figure 3.6 depicts the proposed ANN architecture. It consists from input, output, and hidden layers. Since data is time series, the input can be a number of past demand values. Also the output it fed back together with its past values as inputs. If input is $u(t)$, the output can be written as follows:

$$y(t) = f(u(t-1),...,u(t-d_1),y(t-1),...,y(t-d_2)) \tag{3.1}$$

where d_1 is the time delay of the input and d_2 is the feedback delay.

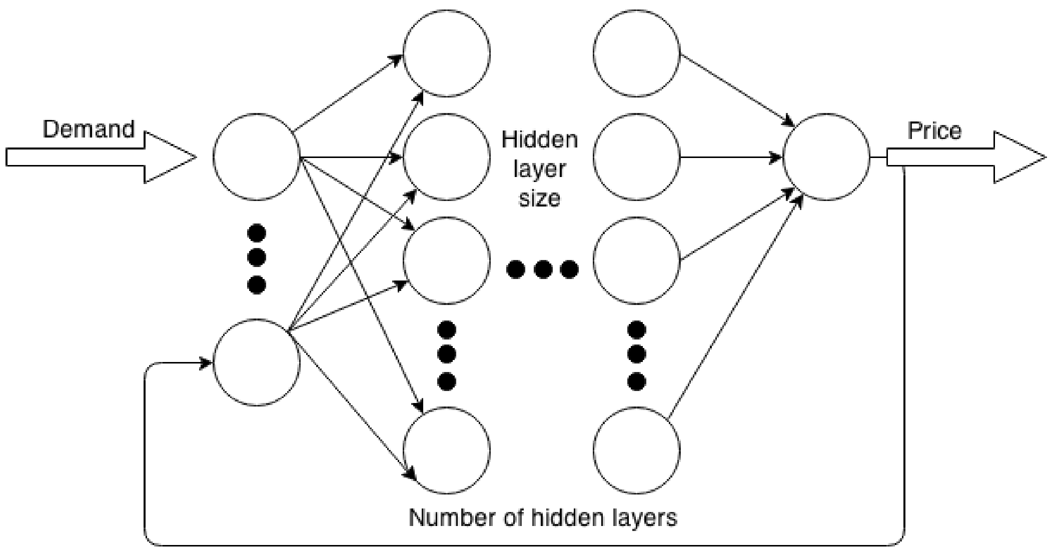

Fig. 3.6 Neural network architecture.

In this experiment the parameters for the NN were chosen arbitrarily to be as follows:

- Single hidden layer size of 100 neurons.
- Input delay of 100 last load values.
- Feedback delay of 40 last price values.

The training was carried out using Levenberg-Matquardt back-propagation (BP) method in Matlab software environment. 20,000 data points were used and the proportion for training, testing and validation was 50%, 15% and 35% correspondingly. The performance function was chosen to be equally weighted Mean Square Error (MSE).

3.2.4 Results

This section describes the results of trained neural network and Fig. 3.7 shows a fragment of how well the output fits training data. The overall performance of neural network is measured by MSE and is equal to 2.2×10^{-6}.

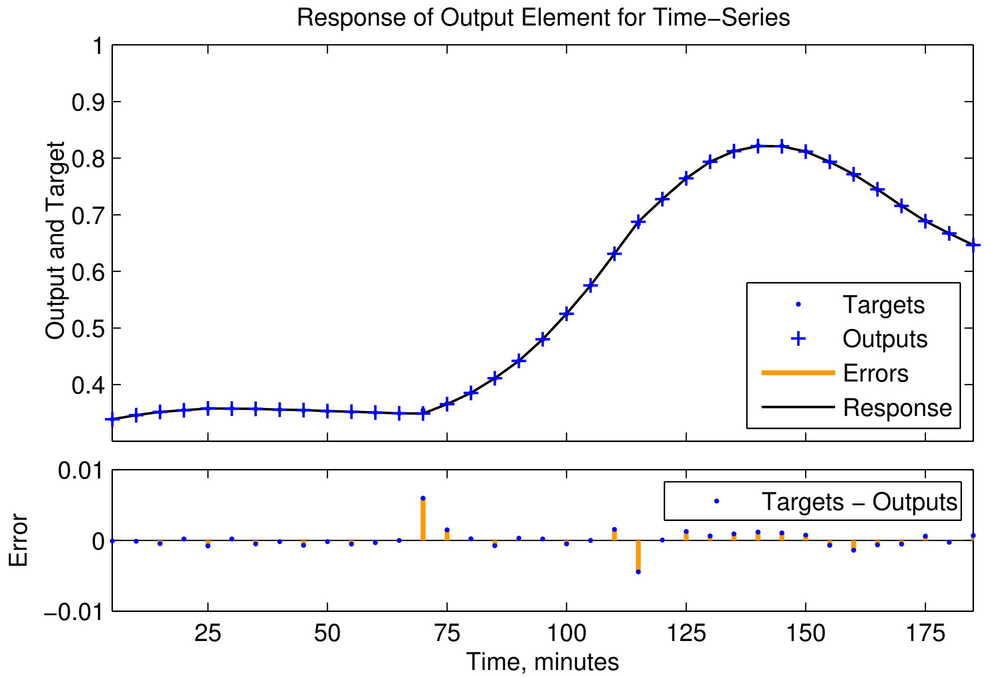

Fig. 3.7 A fragment of NN training results.

Another measure of how well NN performs is the correlation between predicted output and target. Figure 3.8 depicts four correlations for training, validation, testing, and overall data. All cases show perfect results.

It is important not to over-train the network since it can over-fit the training data and poorly perform on new data. Figure 3.9 shows training performance for different data sets versus training iterations (epochs). The network performs best after 9 iterations.

Since the data is considered as time series and NN is with feedback loop, it is important to check autocorrelation of errors to make sure NN is properly trained. Ideally it is desired that non-zero lag fall into 95 % confidence interval. Figure 3.10 displays autocorrelation of errors in this experiment. The results are considered to be acceptable.

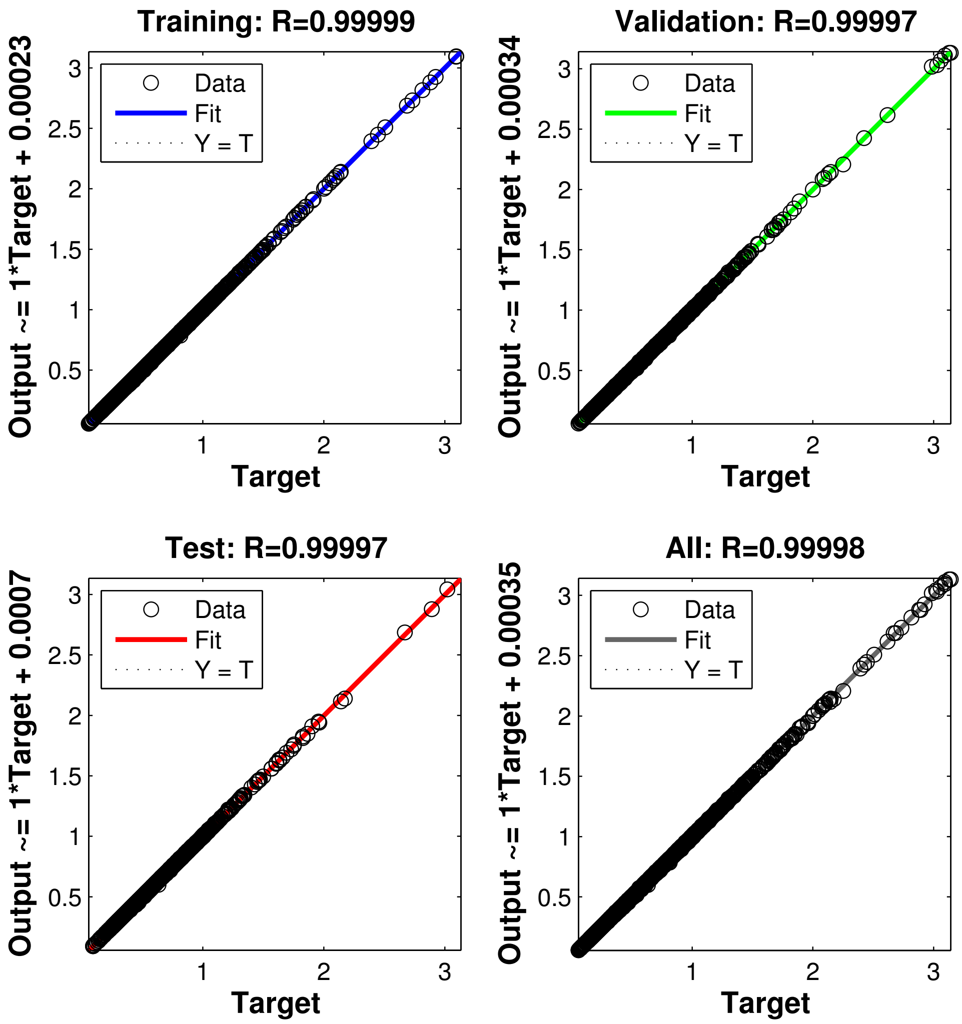

Fig. 3.8 NN training, validation, test data point and overall output-target correlation.

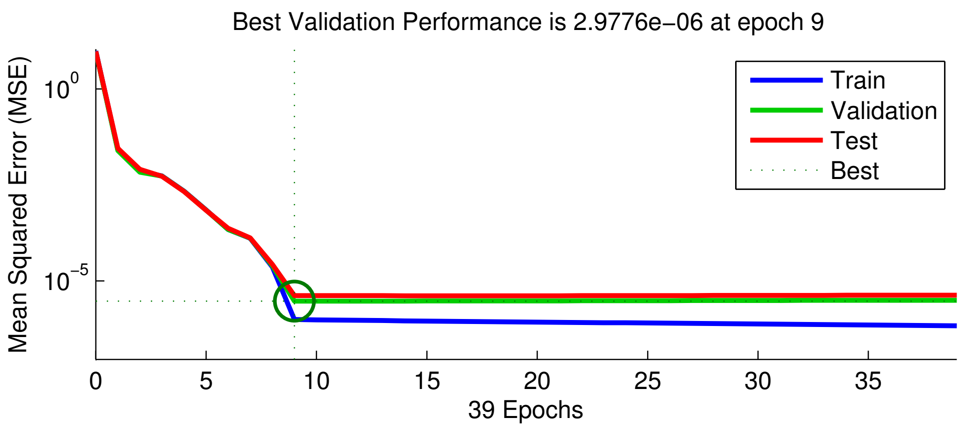

Fig. 3.9 Neural network training performance.

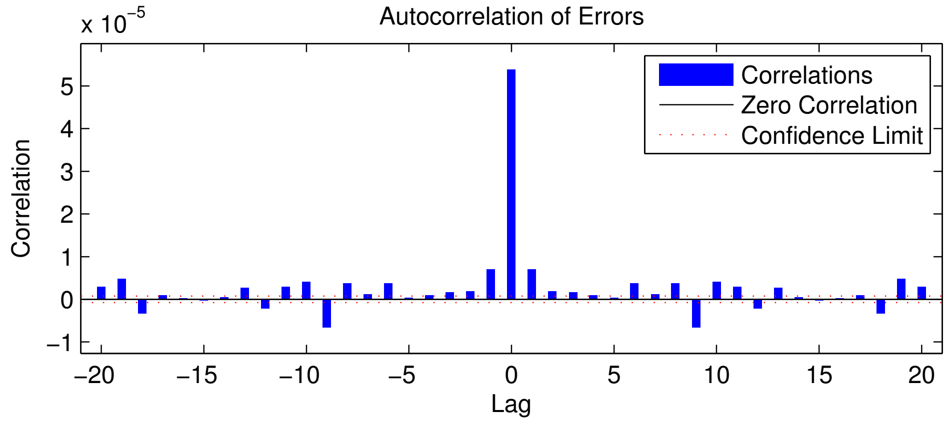

Fig. 3.10 Error Autocorrelation.

Another test was done to validate neural network's performance. Figure 3.11 shows a fragment of NN response to data that was not used during the training. As it can be seen, the response errors are not much different from the errors in the training data set. This indicates that NN is not tailored to a specific data set, i.e. overtraining has not occurred.

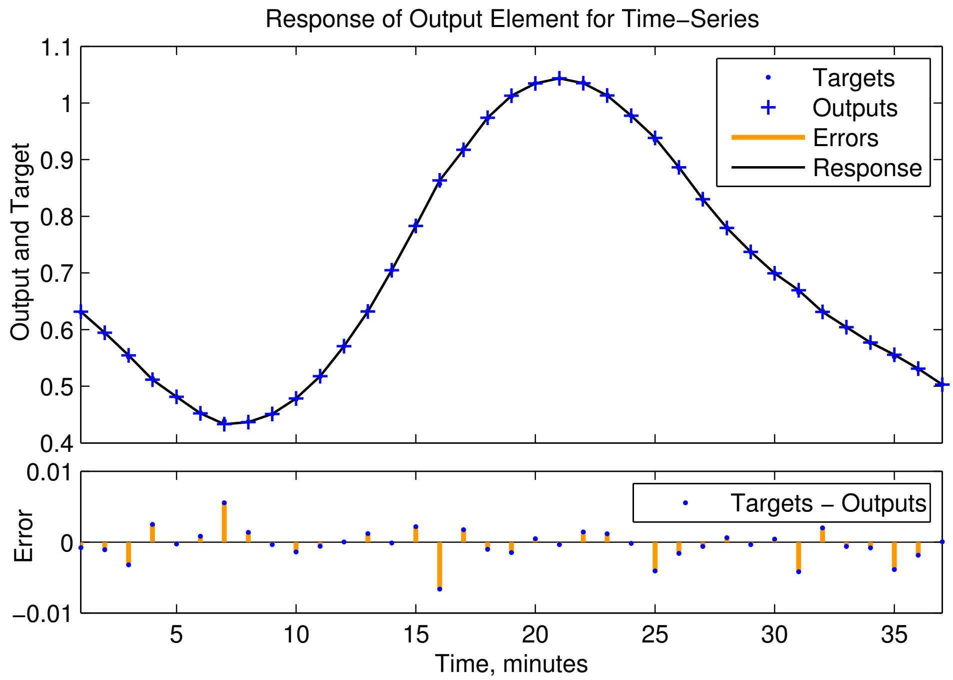

Fig. 3.11 A fragment of NN response to validation data set that was not used during training.

The training of NN aims to minimise the cost function of one-step ahead prediction. This highly minimises the required training time and computational efforts. However, the purpose of the trained neural network is to predict a couple of steps ahead. It is obvious that when predicting more than one step, the errors accumulate and predictions become less accurate. Figure 3.12 indicates the performance in a closed loop NN setup, i.e. the feedback loop uses the values computed by the NN instead of the target values. The chosen fragment illustrates how prediction error increases but the prediction trend is very similar to the target trend.

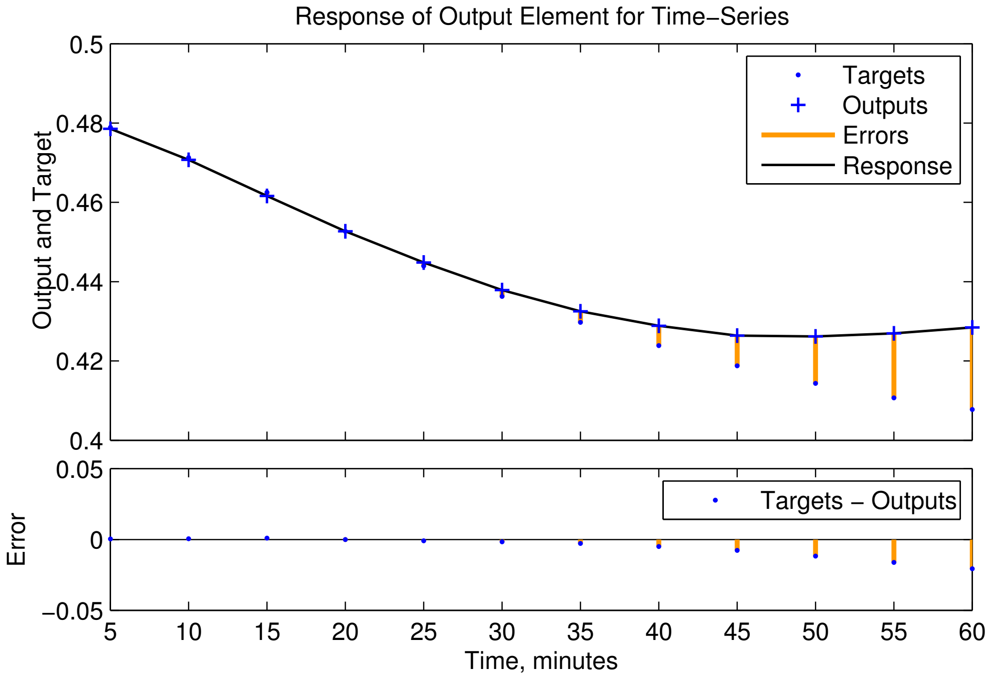

Fig. 3.12 An example of NN response using closed loop NN architecture - 60 min ahead prediction.

Another test was carried out to estimate how far ahead this NN can predict. A data set of 1000 time steps was used to compute Mean Absolute Percentage Error (MAPE) and correlation value R dependency on time delay. Also zero effort prediction was used to evaluate results of NN. Zero effort prediction assumes that the predicted value is simply the latest known target value, i.e. prediction is kept at a constant level.

Figure 3.13 compares MAPE of NN with MAPE of zero effort prediction. It can be seen that NN performs better until about 55 minutes ahead. Similarly, Fig. 3.14 compares the correlation R values. In this case the NN performance is better in all the range that was tested (60 minutes).

To further illustrate the correlation of predicted prices versus the target prices, four plots were added in Fig. 3.15. It shows how predicted values at 5 min, 15 min, 30 min, and 1 hour into the future correlates with target values. It is clear that the NN performs well up to at least 30 minutes forecast.

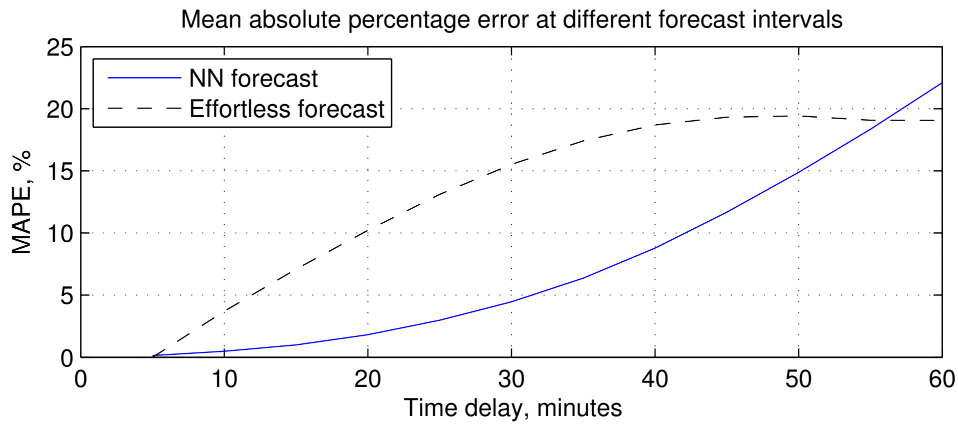

Fig. 3.13 Mean absolute percentage error at different forecast intervals.

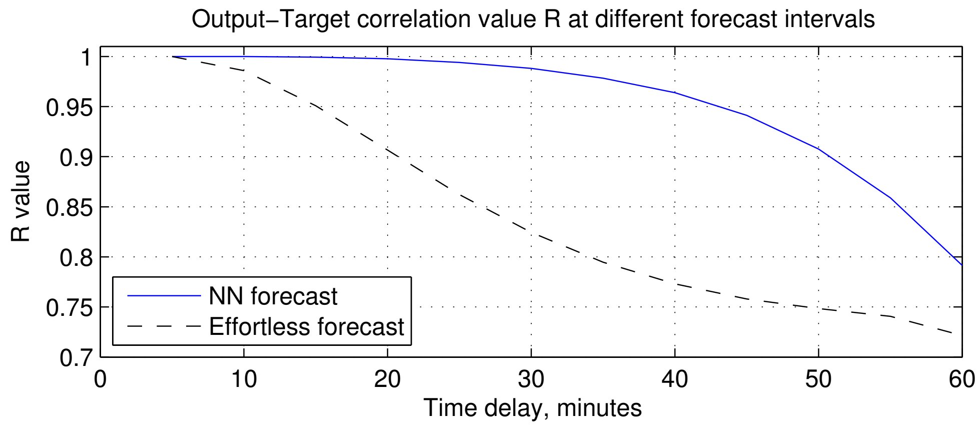

Fig. 3.14 Output-Target correlation at different forecast intervals.

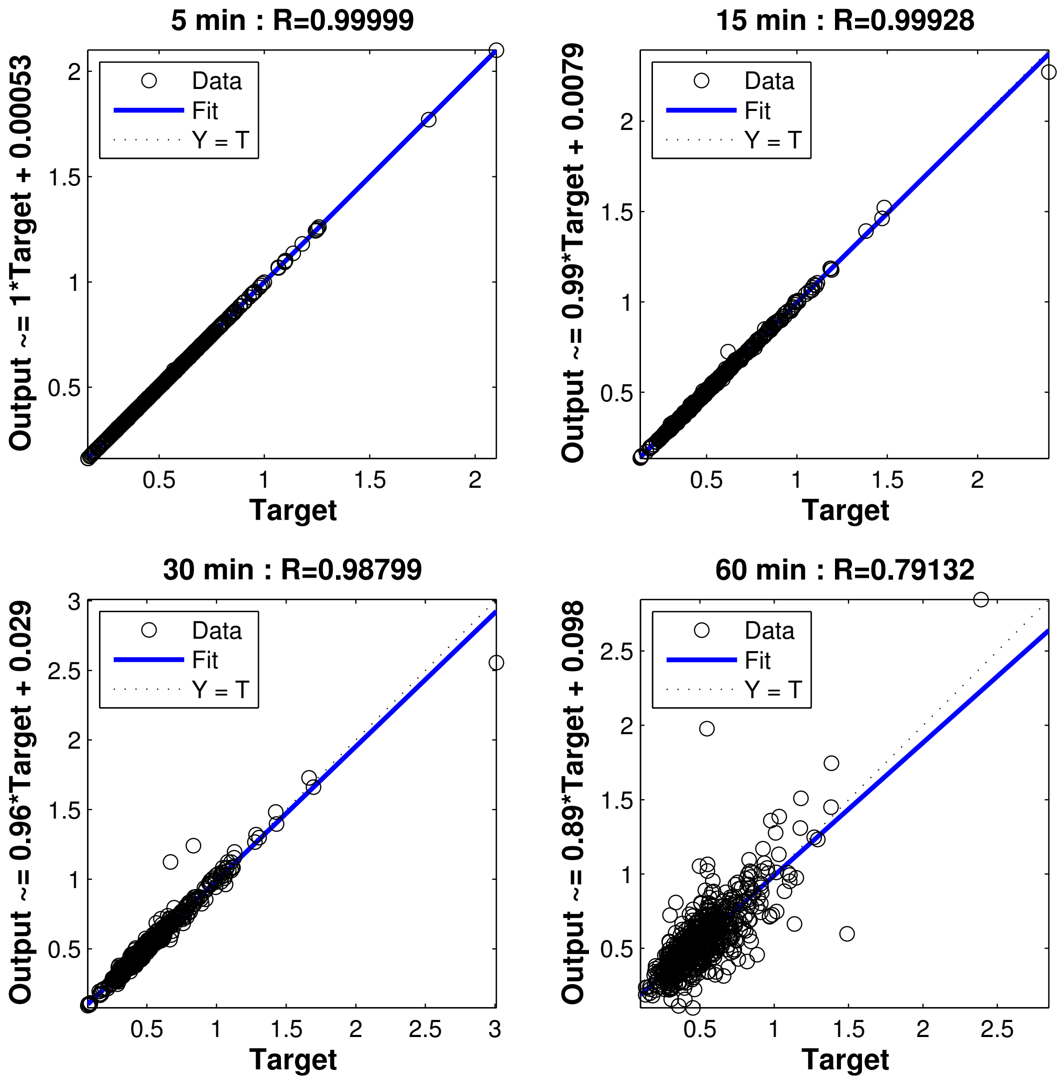

Fig. 3.15 5 min, 15 min, 30 min, and 60 min ahead prediction correlation with target values.

3.2.5 Conclusion

In this paper, the ability to learn price to load relationship in a demand response scenario using neural networks is analysed. It is proposed that artificial intelligence can be used to model system response to price change. Early stage research has given satisfying results and trained NN showed the ability to precisely predict prices required to reach a certain load for at least 30 minutes ahead.

Acknowledgements

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Chapter 4

Forecasting Hot Water Consumption in Dwellings

4.1 Usage of Forecasting Results

As the previous chapter introduced the use of artificial neural networks for modelling price and load relationship, this chapter further extends the use of artificial intelligence. At first, similar topology ANNs are tested in thermal load forecasting application. It analyses the results on residential hot water consumption - both individual house level and aggregate consumption. Secondly, traditional forecasting methods are also applied in comparison to ANNs. The work done in this chapter enables the design of smart hot water heaters in the consecutive chapter because forecasting is the heart of the controller. The best performing model is chosen and later used in the development of thermal demand response device.

4.2 Forecasting Hot Water Consumption in Dwellings Using Artificial Neural Networks

Forecasting Hot Water Consumption in Dwellings Using Artificial Neural Networks

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Abstract

The electricity grid is currently transforming and becoming more and more decentralised. Green energy generation has many incentives throughout the world thus small renewable generation units become popular. Intermittent generation units pose threat to system stability so new balancing techniques like Demand Side Management must be researched. Residential hot water storage heaters are perfect candidates to be used for shifting electricity consumption in time. This paper investigates the ability on Artificial Neural Networks to predict individual hot water storage heater energy demand profile. Data from about a hundred dwellings are analysed using autocorrelation technique. The most appropriate lags were chosen and different Neural Network model topologies were tested and compared. The results are positive and show that storage water heaters could potentially shift electric energy.

4.2.1 Introduction

Electric power grid is the largest device ever made by a human being, where it plays an enormous role in every person's life. Traditional power system was designed to be centralised and consists of large generation units generating electricity and many consumers using it. This concept has been gradually changing over the years, particularly with distributed energy resource systems.

The grid is currently transforming into so called the Smart Grid. Consumers are becoming prosumers, meaning they not only consume, but also generate electricity. Electricity now flows both ways (from the grid to the consumer or from consumer to the grid) and the grid could also contain smaller generating units. In Europe, there have been many incentives for wind and solar power pants to be built [SWN14]. But aside of all the environmental advantages of green energy, there are considerable drawbacks of renewable energy generators. The biggest one being the fact that renewable energy generation is intermittent (or forecast) or very hard to control compared to conventional power generation.

This intermittent nature greatly increases the complexity of the supply demand balancing problem. Increasing number of renewables poses real threat to system resilience and affect system stability [NJ13]. To counterweight this issue either more spinning reserve power plants should be built or other alternatives researched and found. This has invoked great attention from researchers around the world.

The authors of this paper are looking into new ways to balance electric energy while keeping current infrastructure and thus minimising upfront cost [Str08]. In fact the balance should be reached not only by increasing or decreasing generation, but also by changing how people consume electricity. This modification of consumer demand profile through various incentives or education is generally called Demand Side Management (DSM). This term dates back to early 1980s [Gel85], but the attention on it is increased recently due to several reasons. Electricity market deregulation was the first step towards enabling DSM, but the recent attention is mainly due to the development of Smart Grid. The addition of additional communication layer on top of existing power grid allows more precise management and control of electricity. It is expected that the future grid will be able to monitor and control appliances in residential houses. Thus residential customers are allowed to contribute in system balancing act.

There are several kinds of DSM programs. The most popular ones can be grouped into Price Based programs (PBP) and Incentive Based Programs (IBP) [AES07]. Programs can differ in many aspects. As the group names suggest, some programs are based on Real Time Price (RTP) [GL14], some give incentives like bill discounts. Some require Direct Load Control (DLC) while others leave customer to make the final decision when to curtail. There are also differences in how many appliances can participate in every residence [RFFA12]. All in all, every incentive in DSM program boils down to decreased energy bill.

There are devices in every house that are flexible in terms of when the electricity could be used, i.e. energy use can be shifted in time. One of the biggest electricity users in dwelling is an electric hot water heater [NW15]. Also due to its large inertia, it can be turned on at different times without a notable change in temperature [EGP12]. This makes it a perfect device candidate that could be used for helping system in reaching perfect balance while optimising existing generation resources.

For electric water heaters to be able to fully participate in demand side management, the first step is to be able to understand how individuals consume hot water. To be more specific, it is required to be able to predict or forecast how every single dwelling or a group of similar dwellings consume hot water. In this particular paper authors are looking into the ability of Artificial Neural Networks (ANN) to learn and predict the hot water consumption patterns in dwellings [AHA+14, EGP11]. Having accurately forecast hot water consumption patterns in dwellings, it will then be able to optimally control electricity consumption to maximise supply demand balance by efficiently using existing generation capacity [SKM+13, KS14a].

4.2.2 Demand Side Management using Hot Water Usage

There are several reasons why hot water heaters are well suited for the use of demand side management of electricity [AHP12]. Hot water heaters (boilers) are installed in majority of residential houses, lowering the initial installation cost as the infrastructure is already established. Also this makes energy storage distributed and closer to the end user. Secondly, water has high specific heat that allows storing relatively large amount of energy. This enables large power deviations from normal consumption for a reasonably long period. Finally, resistive hot water heaters are very efficient in terms of energy conversion from electrical to thermal energy, i.e. all electrical energy goes to heat. Losses are only experienced due to thermal conductance through storage tank insulating walls, thermal losses in pipes or resistive losses in wires feeding the device. This fact should be emphasised in cold climate regions.

Sandels et. al in [SWN14] presents a model for forecasting Domestic Hot Water (DHW) and other types of consumers based on non-homogenous Markov chains. The results of the DHW module coincide with the measured consumption, thus confirms that the model is reliable. Another study in [NJPH07] focuses on voltage control to reduce domestic hot water loads. In [GMF99], DHW load profiles are simulated using physical models and then Direct Load Control (DLC) switching programs are evaluated for how load-shedding actions change customer comfort level. A peak load reduction is studied in [vTL96] using Time of Use (TOU) and other techniques.

4.2.3 Data used for forecasting model

The data used in this paper was taken from a project initiated by the Energy Monitoring Company in conjunction with and on behalf of the Energy Saving Trust, with funding and support of the Sustainable Energy Policy Division of the Department for Environment, Food and Rural Affairs (Defra). The data consists of temperature and volumetric consumption records from 112 different dwellings. Various sensors were fitted in houses that measured hot water volumetric consumption, inlet temperature, outlet temperature and primary circuit temperature (in regular boilers). Some additional devices measuring water temperature were fitted around pipes near kitchen sink, washing machine, bathroom basin, bath, etc (Fig. 4.1). This allowed determining the exact spot in house where energy was used. Also boiler type, geographical region, number of occupants and other parameters were recorded.

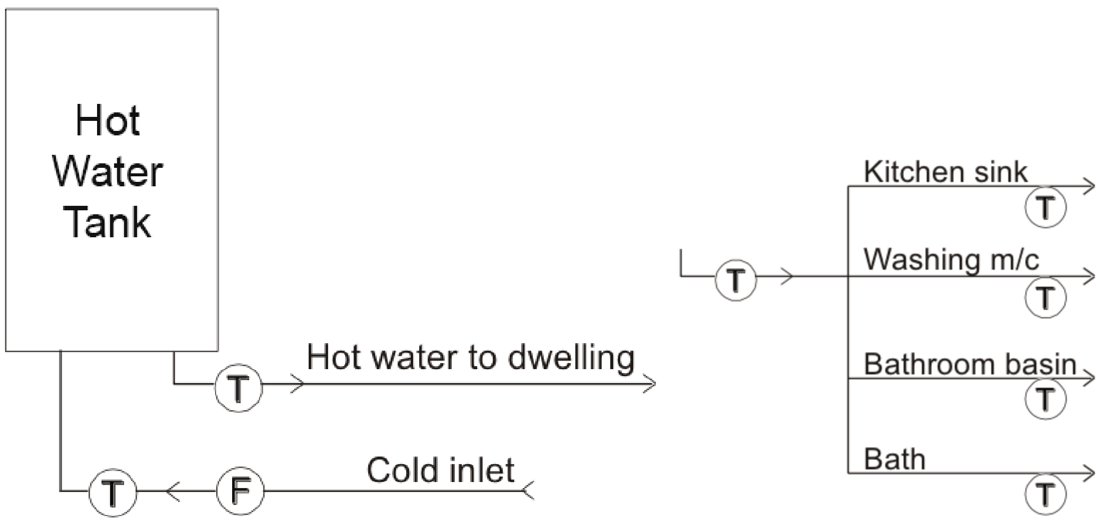

Fig. 4.1 Various sensor layout inside dwellings [ene08].

For this particular paper it was not desired to consider the location of water use. Instead the interest was focused on the total volumetric and energy consumption of hot water boilers and hence only hot water meter readings and inlet/outlet temperatures were used. Water meter was aggregated for different sampling periods because it was being reset after every reading. Since inlet and outlet temperatures are not constant, the volumetric consumption does not show the exact energy consumption. To calculate the energy consumed it is required to look at both volumetric consumption and difference in temperatures. The following formula was used to calculate energy consumed:

$$E_t = (T_{out} - T_{in}) * V_t * \rho_w * C_w \tag{4.1}$$

where E_t is the energy stored in water used at time t, Tout and T_{in} are the outlet and inlet temperatures respectively, V_t is the water meter reading at time t, ρ_w is the water density, and C_w is the specific heat of water.

4.2.3.1 Formating Raw Data

Data of domestic hot water consumption in dwellings were recorded in year 2006. The data was recorded for about one year period at ten minute intervals. When water run-off was detected, the sampling rate increased to five seconds. The data was then resampled at constant intervals of 1, 2 and 3 hours. A range of periods was chosen to test for the best accuracy. The volumetric records where aggregated for every sampling period. Data was then looked through and any outliers or inconsistencies were discarded to improve the quality of the data which is going to be used for the model.

4.2.3.2 Further data analysis

In this paper authors are testing the ability off ANN to learn hot water consumption and predict future consumption. Neural Network Nonlinear Autoregressive (NAR) and Nonlinear Autoregressive Exogenous (NARX) models were tested, where autoregression is the key element in this forecast.

The next step in analysing the data was to look at auto-correlation of every single dwelling separately. Different patterns were noticed, where Fig. 4.2 shows the first type of auto-correlation when the volumetric hot water usage correlates at every 24-hour interval. This means that occupants of this particular dwelling have strong periodic habits because their water usage follows strong pattern and is repetitive.

Another type of dwelling that can be distinguished is when consumption pattern repeats every 6 hours. In Fig. 4.3 the data autocorrelation has four spikes for each previous day (two positive and two negative). The 12-hour period can be explained that there is a similar consumption during the night and in the middle of the day (consumption is small), and there is a large consumption in the morning and in the evening (12 hours apart). The negative correlation appears every 6-hour because peaks and lows are 6 hours apart.

Fig. 4.2 and Fig. 4.3 represents only two dwellings. To represent autocorrelation of all dwellings, a box plot diagram was used. Fig. 4.4 shows a box plot diagram of autocorrelation with a maximum lag of one week. Each box represents how the dataset

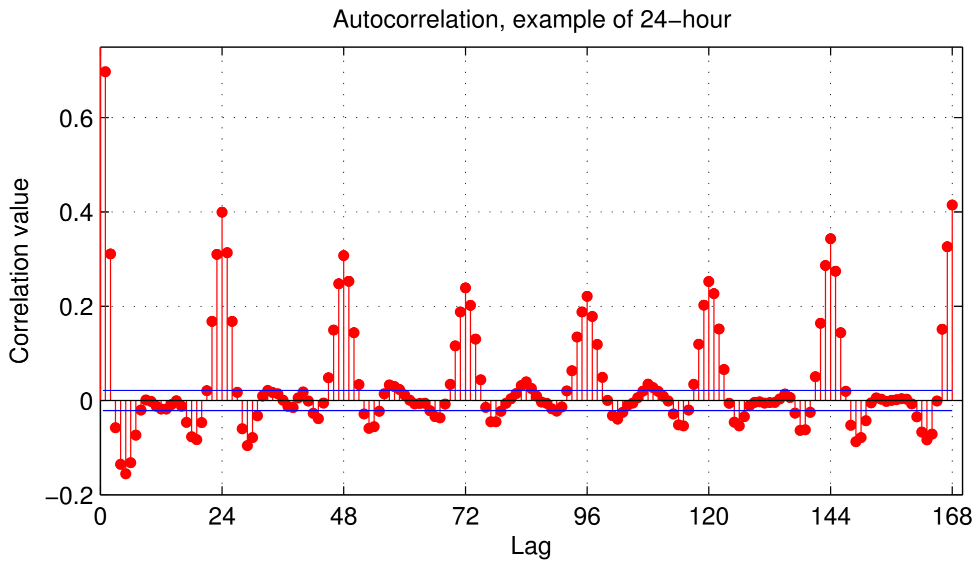

Fig. 4.2 Autocorrelation example, when data best correlates at 24 hour intervals.

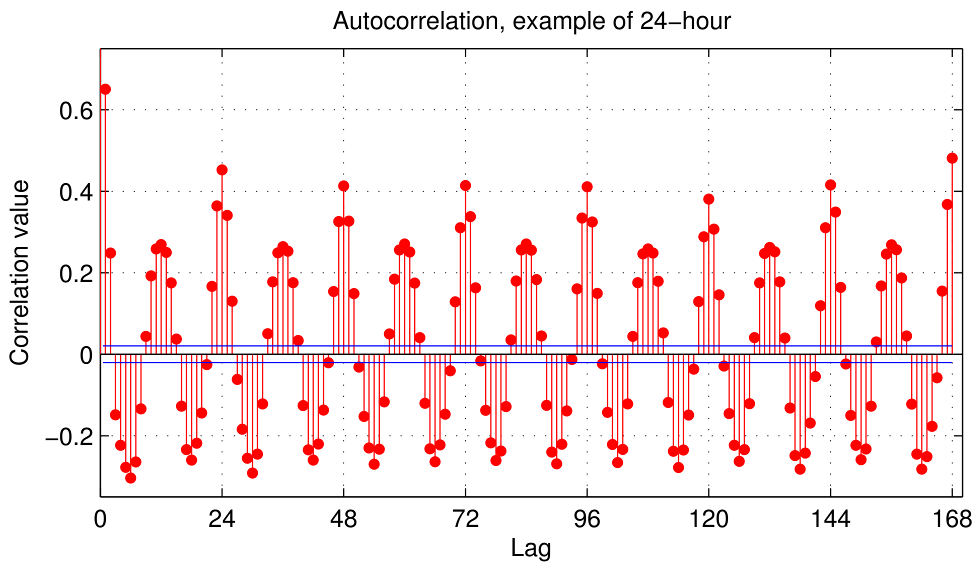

Fig. 4.3 Autocorrelation example, when data best correlates at 12-hour and 6-hour intervals.

for particular lag is distributed and the median is represented by the red lines. Red crosses represent the outliers. It can be noticed there is a higher peak at 168th hour (mean correlation value 0.3528), which is the lag of 7th day, comparing with the same hour in every other day of the week (mean correlation value 0.2721), i.e. the data repeats best every week. This shows that not every day in a week looks the same.

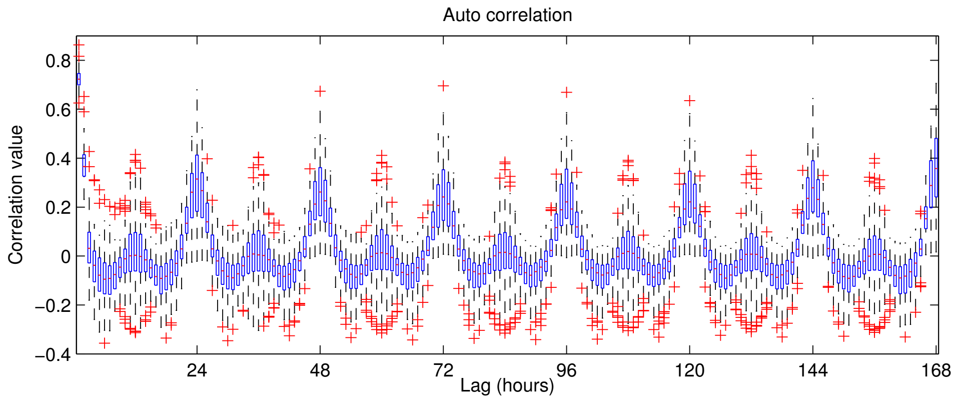

Fig. 4.4 A box plot of autocorrelation data of all dwellings hourly data.

The mean value of autocorrelation (period of one week) was calculated for every dwelling and arranged in an ascending order as shown in Fig. 4.5. According to the result, no separate regions could be distinguished – the correlation values are distributed evenly.

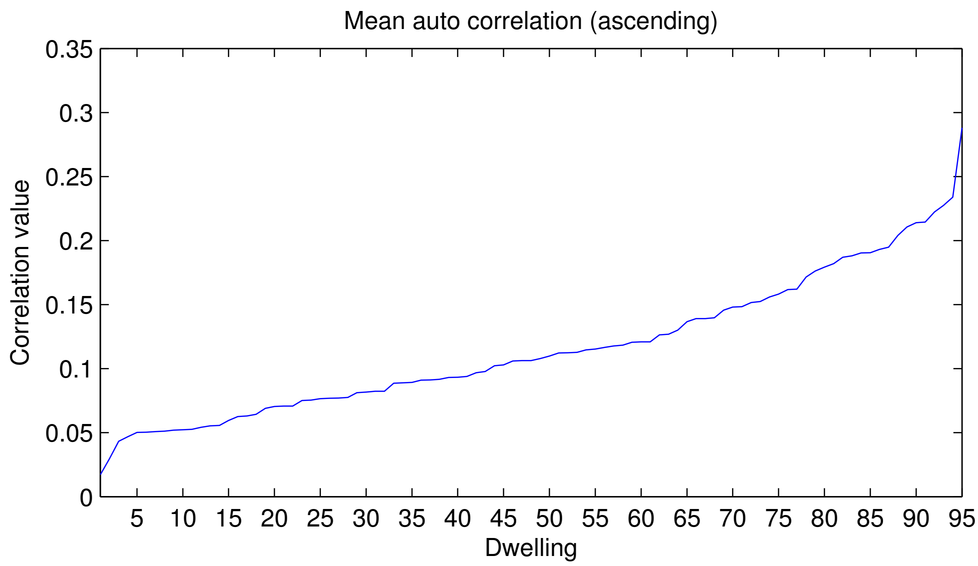

Fig. 4.5 Mean autocorrelation in an ascending order.

As mentioned above, hot water consumption differs depending on the day of the week. Weekly mean consumption pattern was calculated and is shown in Fig. 4.6. It can be seen that consumption profile of Monday to Friday is different from profile of Saturday and Sunday. Further analysis has been carried to investigate this (Fig. 4.7).

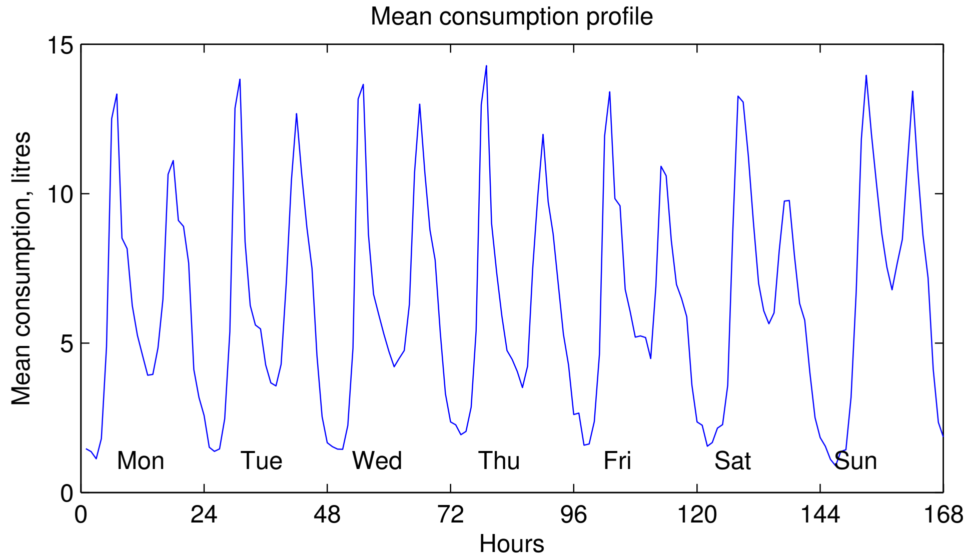

Fig. 4.6 Weekly mean volumetric hot water consumption pattern.

Fig. 4.7 shows cross-correlation R-values between different days of the week. First of all, it could be divided into two regions using the diagonal. The values above the diagonal were calculated for correlation between weekdays of the same week, whereas the values below the diagonal (inclusive diagonal) are calculated using weekdays of consecutive weeks. Therefore, the matrix is not symmetric.

By looking at the calculated R-values, the matrix can be further divided into 4 regions. The values in region 1 (top left) are between 0.21 and 0.28 – it represents high correlation between consumption profiles of Monday to Friday. Region 2 (top right) and region 3 (bottom left) with low R-values (0.11 to 0.14) correspond to low correlation between working days and weekends. On the other hand region 4 (bottom right – values 0.16 to 0.19) shows that water usage on Saturdays and Sundays are similar. Conclusion could be drawn that ANN needs external input giving information about the day of the week.

4.2.4 Artificial Neural Network Forecasting Technique

An ANN model was created in MATLAB programing environment. To forecast hot water consumption, ANN technique was chosen for couple of reasons. ANN is a learning algorithm that can be adapted to different consumption profiles. The goal is to learn individual consumption habits of families and maximise the amount of energy that could potentially be shifted in time to reduce the overall peak seen by the generation or to better match the demand with supply. Secondly, ANN learning algorithm is very appealing

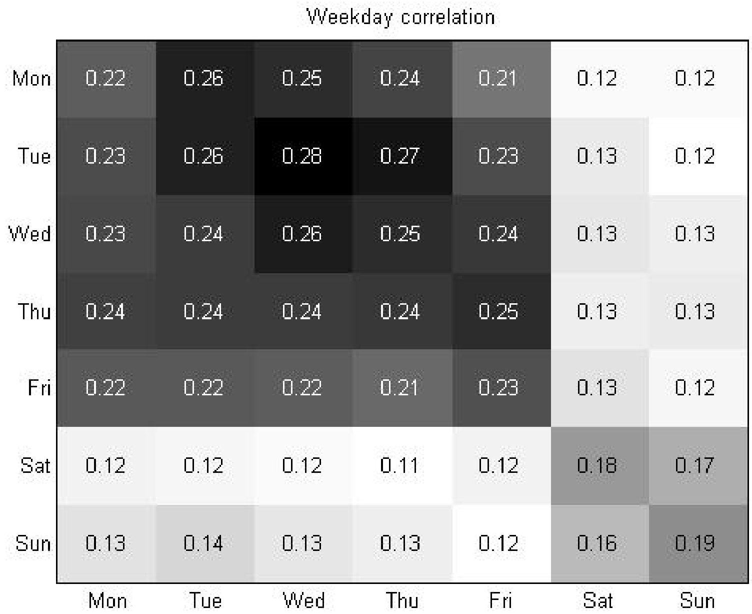

Fig. 4.7 Weekday correlation.

because it mimics nature. Although, it is a high level algorithm that requires a relatively large amount of processing power, which nowadays becomes easily available [vTL96].

4.2.4.1 Time-series forecasting using NAR model

A NAR model was created using one hidden layer with 10 neurons, where Fig. 4.8 shows a simplified model diagram. The data division for training, testing and validation was chosen to be random for these time series. The performance was measured using Mean Square Error (MSE). ANN was trained using Levenberg-Marquardt training algorithm. An individual dwelling hourly volumetric hot water consumption time series were used to train the network. According to auto-correlation analysis, different sets of lags were tested to find the best performance. The lag configuration in the first 10 cases was in ascending order in difficulty (see Table 4.1).

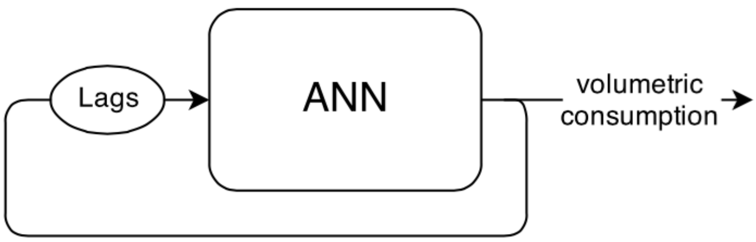

Fig. 4.8 Simplified NAR model.

Table 4.1 The R-values of NAR and NARX models for different cases.

Case	Lags (NAR)	Mean R values			
		NAR	NAR ext.	NARX	NARX ext.
1	[24:24:24*6]	0.49	0.49	0.58	0.58
2	[24:24:24*7]	0.52	0.52	0.58	0.58
3	[24:12:24*7]	0.53	0.53	0.58	0.58
4	[24:6:24*7]	0.54	0.53	0.59	0.58
5	[1 24:24:24*7]	0.77	0.77	0.79	0.80
6	[1 24:24:24*7 24*7+1:24*8]	0.79	0.79	0.80	0.80
7	[1:23 24:24:24*7]	0.87	**0.88**	**0.88**	**0.88**
8	[1:23 24:24:24*7 24*7+1:24*8]	**0.88**	**0.88**	**0.88**	**0.88**
9	[2:23 24:24:24*7]	0.74	0.74	0.75	0.76
10	[2:23 24:24:24*7 24*7+1:24*8]	0.73	0.74	0.75	0.74

Case 1 uses only 6 past inputs. Each of them is a past input of exactly the same hour of the day from past six days. Fig. 4.3 suggests that these inputs should have the biggest weight when predicting future consumption. Case 2 has the addition of the 7th day – the same exact hour from the previous week. Figures 1-3 show that there are additional correlation peaks every 12 and 6 hours so cases 3 and 4 have additional inputs of every 12 and 6 previous hours respectively. Case 5 is the same as case 2 with the addition of the most recent consumption reading. Case 6 contains 24 hour consumption profile the same day from previous week. Case 7 and 9 has inputs from the most recent day. Finally, case 8 and 10 contains a combination of 6 with 7 and 6 with 9 respectively.

After ANN ware trained for all dwellings, the output-target correlation R-values were recorded to judge the performance of the model. The simulations for the same 10 cases were repeated with extended lag configurations – for every lag between 24 and 168, there were adjacent lags added: t-1 and t+1. For example instead of lag 48, now ANN receives lags 47, 48 and 49. Table 4.1 in the results section shows the corresponding results for both NAR and NAR extended configurations.

4.2.4.2 Time-series forecasting using NARX model

The ANN was converted from NAR to NARX by adding external inputs (see Fig. 4.9). As the data analysis above suggested, the ANN should be supplied with information containing the day of the week and whether it is a weekend or not. As a result, 6 dummy variables were constructed to represent weekday and additional dummy variable was used as a Boolean for marking weekends. Also, average hourly consumption profile (average value for the hour that is being predicted) was fed in as an external input.

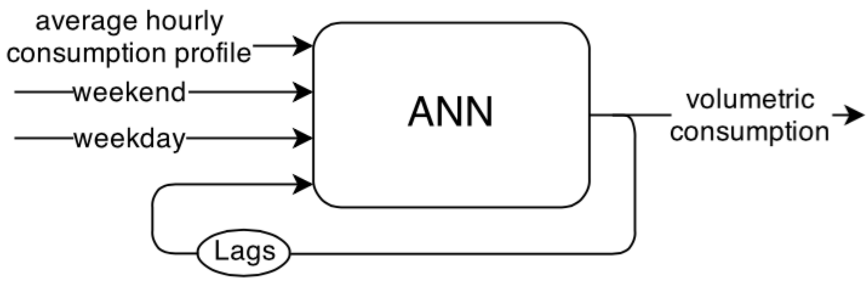

Fig. 4.9 Simplified NARX model.

The simulations were then run again using lags from previous 10 cases and the results can be found in the following section.

4.2.5 Results

The extended data analysis was focused on autocorrelation. The results are as expected and show that daily volumetric hot water consumption in dwellings is similar. It is also clear that water usage habits during workdays and weekends are different (Fig. 4.7).

The goal of this paper was to assess the ability of ANN to predict hot water consumption for separate dwellings. Fig. 4.10 depicts how well NAR model predicts. It can be seen from the boxplot that cases 1 to 4 are quite unreliable as there is a large spread in performance variable (R value) throughout dwellings. On the other hand cases 5 to 10 show that NAR model performs well and the R-values are about 0.8 with a narrow spread.

Finally, Fig. 4.11 compares results between NAR and NARX models. It can be seen that NARX model predicts better in all cases, though the relative difference is minute in some cases. By looking at Table 4.1, it can be seen that cases 7 and 8 perform the best.

Acknowledgement

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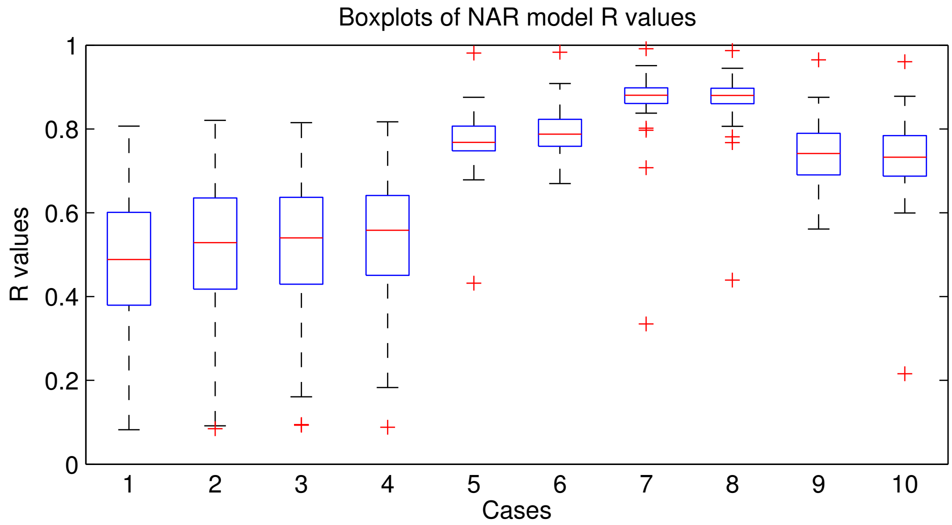

Fig. 4.10 Boxplot of output-target correlation R-values, NAR model simulation.

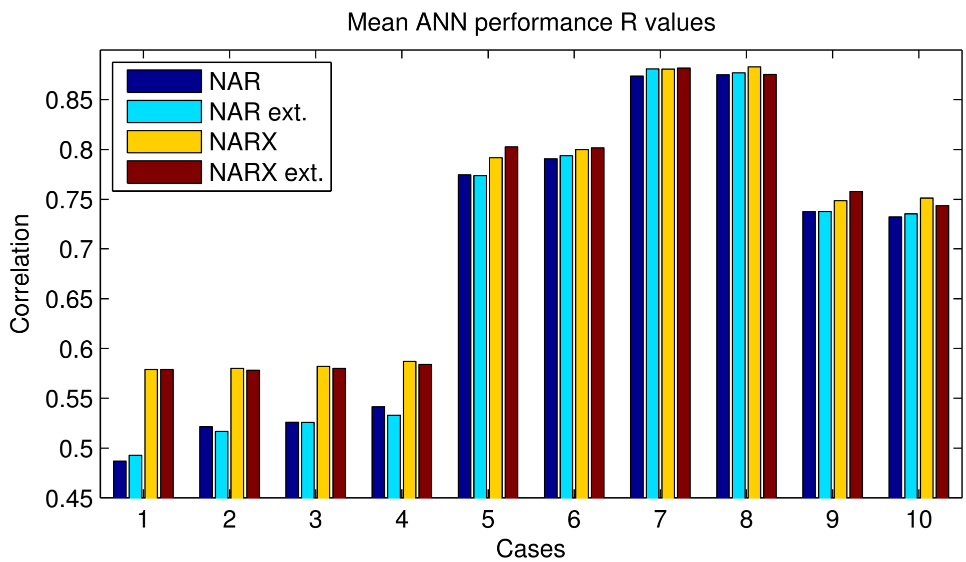

Fig. 4.11 Mean R values from all simulations. Graphical representation of Table 4.1

4.3 Forecasting Hot Water Consumption in Residential Smart Houses

Forecasting Hot Water Consumption in Residential Smart Houses

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Abstract

An increased number of intermittent renewables poses a threat to the system balance. As a result, new tools and concepts, like advanced demand-side management and smart grid technologies, are required for the demand to meet supply. There is a need for higher consumer awareness and automatic response to a shortage or surplus of electricity. The distributed water heater can be considered as one of the most energy-intensive devices, where its energy demand is shiftable in time without influencing the comfort level. Tailored hot water usage predictions and advanced control techniques could enable these devices to supply ancillary energy balancing services. The paper analyses a set of hot water consumption data from residential dwellings. This work is an important foundation for the development of a demand-side management strategy based on hot water consumption forecasting at the level of individual residential houses. Various forecasting models, such as exponential smoothing, seasonal autoregressive integrated moving average, seasonal decomposition and a combination of them, are fitted to test different prediction techniques. These models outperform the chosen benchmark models (mean, naive and seasonal naive) and show better performance measure values. The results suggest that seasonal decomposition of the time series plays the most significant part in the accuracy of forecasting.

4.3.1 Introduction

The global population growth rate was estimated to be about 1.096% in 2012 [Age12]. This rapid development of the human population, increased number of buildings and technological advancement in energy-intensive applications are causing fast electric energy consumption growth [AHA+14]. The traditional fossil fuel-based energy generation increases the emissions of greenhouse gases, and as a result, green energy generation technologies are adapted. Similarly, many incentives are being implemented to help the development of clean energy [AL04].

Renewable energy generation output is hard to control due to its intrinsic intermittency and uncontrollable primary energy source (wind, sun, tides) [YZXC11]. As a result, wind, solar or other renewable energy generation requires a large amount of backup power to compensate variability [Str08]. The traditional fossil fuel-based spinning reserve would contradict the aim to lower carbon emissions, so other solutions are needed.

There are two primary ways to avoid, if not minimise, the renewable energy balancing issue. For example, large-scale energy storage facilities could help to shift energy in time, but this requires a large amount of investment and usually high maintenance and running costs [Str08, McD01, FMS+12]. Secondly, interconnectivity could lower the total generated power variability. The larger the system, the lower the statistical variation and volatility of the total generation and consumption of electricity [JAW+12], as long as there is no significant correlation between intermittent energy outputs [POG+05]. In general, interconnected geographically-distant generating units have lower correlation, thus total power variability is reduced.

There are also other techniques to strengthen system backup; however, the forecasting analyses represented in this paper are aimed to serve the required information for future development of demand-side management (DSM). This paradigm potentially aims to solve the energy balancing problem from the consumer side instead of actively controlling the generation and transmission [Kar11]. It has the potential to increase system efficiency and power quality, while reducing system vulnerability and, hence, helping to conserve energy [JAW+12].

Demand-side management is a concept related to the control of residential and industrial appliances to maximise the use of energy. The DSM term was publicly introduced in the early 1980s [Gel85], though a lack of IT and communication infrastructure limited its full potential until the early 21st century. It involves peak shaving, valley filling, load shifting and other load profile transforming techniques [MGdAdCL15, GG14]. End users could participate in DSM through price-based DSM programs (lower tariffs), direct control-based programs (various incentives or benefits to the user in return) or partial direct control (the user would release control during certain non-predefined times). End users tolerate different discomfort levels, thus individual agreements are needed between the system operator and the consumer.

Residential appliances could be classified as shiftable and non-shiftable loads. For example, lighting is a non-shiftable category, because it would greatly degrade comfort if not used when needed by the user. On the other hand, users are not very sensitive to small changes, such as the temperature setpoint of a hot water heater. Hot water heaters are commonly-used devices in most houses, where water has a large specific heat capacity enabling control relatively easily. Previous research suggests that domestic hot water (DHW) accounts from 7.5% to 40% [BHGK09, NW15] of total domestic energy usage. These properties make hot water heaters a perfect candidate appliance to participate in DSM and system balancing [DL11, PLC10, SP08], hence, the need to focus on hot water demand forecasting.

Currently most hot water tanks are controlled in a very archaic way: Water is maintained at a constant temperature setpoint. It is obvious that there are patterns of hot water usage profiles, and water should not be kept at its highest temperature at all times. The authors of this paper propose that it is possible to forecast individual dwelling hot water consumption profiles and, hence, to potentially participate in DSM. By knowing when hot water is needed, it is then possible to lower the setpoint temperature at certain times [KHP15]. This would enable the water heater appliance to participate in a DSM program. For example, there would be a range of temperatures in which water could be varied, thus changing each individual's electricity consumption profile to reach the system balance [GZ14]. If the range of comfortable temperatures is wide, the appliance has more flexibility in responding to DSM. Therefore, there is a key need for accurate individual hot water consumption forecasts, which is researched in this study.

The section above indicates the need for DHW forecasts and the potential of DHW being used in DSM applications. The remainder of the paper is focused on analysing and predicting time series data. The work is organized as follows. In Section 4.3.2, previous studies are reviewed and the need for individual DHW consumption forecasts is indicated. Section 4.3.3 describes data preparation, model selection and performance evaluation. In Section 4.3.4, the data are analysed, including tests for time series stationarity and seasonality. Section 4.3.5 shows the results of model performances, and Section 4.3.6 overviews the findings. The work is concluded in Section 4.3.7.

4.3.2 Previous Studies

This section reviews the previous research related to hot water consumption forecasts. The first part includes studies focused on forecasting electricity demand caused by DHW, whereas the second part reviews research related to forecasting thermal demand and demand response (DR).

Sandels *et al.* [SWN14] presented a simulation model for DHW that forecasts load profile. The DHW module is based on non-homogeneous Markov chains, where occupants change states within certain probabilities overtime. Those states correspond to certain activities at home that require a specific amount of energy. Only two activities, taking showers or baths, were taken into account, although there are other ways that hot water consumption could occur, for example hand washing or manual dish washing. Heat loss from the hot water tank was also taken into account.

Some other researchers [AHA^{+}14] demonstrated electrical energy forecasting using artificial intelligence (AI). Support vector machine (SVM) and artificial neural network (ANN) methods were considered, including hybrids of both. Furthermore, some others used SVM and ANN to forecast 24-h electricity loads for individual houses [GZ14]. Javed *et al.* also used ANN to predict the load and compared model performances with the results of traditional model, such as generalized autoregressive conditional heteroskedasticity (GARCH) model, exponential smoothing (ETS) and multiple linear regression [JAW^{+}12]. They stressed the importance of individual forecasts with no data aggregation between houses. The use of ANN was also demonstrated by Bartecsko-Hibbert *et al.* to predict the temperature characteristics of DHW [BHGK09].

Simple forecasting techniques are required in order to compare the relative performances of a more sophisticated model and to serve as a benchmark. For example, De Felice and Yao demonstrated short-term load forecasting and chose naive seasonal model as a benchmark [DFY11]. Although the paper presented a forecasting technique for the total load demand profile using hot water consumption only as external inputs, it demonstrated that ANN and seasonal autoregressive integrated moving average (ARIMA) models could be used to deliver short-term energy forecasting.

Negnevitsky and Wong developed an evaluation tool for a DSM hot water system in [BHGK09]. It is capable of simulating the energy peak-shaving technique using unique multi-layer thermally-stratified hot water cylinders. Monte Carlo simulations were used to generate hot water load profiles for the residential users.

The use of DHW control for DSM and peak shaving is also demonstrated in [NJPH07]. Hashem Nehrir *et al.* demonstrated how aggregate electric water heater loads could be controlled to lower the maximum power demand for certain time periods using voltage control. Researchers emphasised the use of aggregated data, focused on control during critical hours, and demonstrated how residential hot water demand management can enhance the power quality and reliability of the overall system.

Popescu and Serban in [PS08] presented domestic hot water consumption forecasting using time series models. The authors were using real world data collected from a block of flats with 60 apartments. It demonstrated that the Box-Jenkins model is capable of forecasting aggregated total thermal power demand for different days of the week.

Bakker *et al.* in [BMHS08] showed that domestic heat demand prediction is crucial for the adoption of micro combined heat and power (micro-CHP) appliance clusters. They used ANN with the input of the previous day and previous week heat demand profile, as well as weather information to predict 24-h ahead.

The authors in [LSC15] show a very recent work based on forecasting volumetric hot water needs at an individual house level. The paper considers eight residences, 30-min resolution and a 12-week model training period. The proposed autoregressive moving average (ARMA) model is compared to the (a) benchmark mean model and (b) moving average on the same day of the week during the last two months [PG01]. It is concluded that the ARMA model gives higher precision and better recovery from large variations (holidays). The authors also stress the need for residential DHW consumption forecasts to enable precise demand response.

Neves and Silva in [NS15] studied the optimal electricity dispatch in a grid consisting of hybrid diesel, renewable generation and the demand response technique for distributed thermal storage. The authors have tested different demand response strategies based on heuristics, linear programming and genetic algorithms. The DHW storage tank model is presented using the energy balancing technique. This leads to the model being lossless and fully mixed.

There is an extensive amount of previous research done on forecasting thermal energy needs as summarised in this section. Most of it investigates consolidated data of a group of consumers. Such data aggregation improves the forecasting performance, but has a disadvantage of concealing the users' individuality. This paper investigates individual hot water consumption profile forecasts, which discloses the diversity of hot water usage at a given time between different consumption locations, which might potentially be beneficial for DSM. The demonstrated methods (such as exponential smoothing, seasonal autoregressive moving average and seasonal decomposition) incorporate confidence levels, which might be used to avoid compromising user's comfort. Another advantage of the forecasting methods used in this paper is the low computational power requirements. Predictions should be computed locally at smart devices, so the requirements for processing capabilities are strict. Advanced forecasting methods, such as ANN, are generally relatively less robust and computationally more expensive, compared to traditional exponential smoothing, ARIMA or seasonal decomposition [AI11].

4.3.3 Methodology

This section will describe the general methodology and techniques used in the data preparation, the model design, the evaluation and the comparison of forecast models.

4.3.3.1 Preparation of the data

The data were collected by the Energy Monitoring Companyin conjunction with and on behalf of the Energy Saving Trust with funding of the Sustainable Energy Policy Division of the Department of Environment, Food and Rural Affairs (Defra), UK [ene08]. The initial dataset contained hot water consumption measurements from about 120 residential houses. The records included temperature information from various locations, where hot water was supplied. Total volumetric consumption was also measured. The data were collected during the years 2006 and 2007.

By visual inspection, some of the datasets were discarded due to erroneous measurements. As a result, there were 95 datasets left. Outliers, as well as any other inconsistencies in the measurements, supposedly from “stuck” sensors, were also discarded.

The sampling rate of initial data was not constant. Measurements were recorded every 10 min, but when a run-off was detected, the sampling rate increased to 5 s. Before any analysis started, the data were resampled at hourly intervals, by aggregating the volumetric consumption of every hour.

The preparation of the data resulted in obtaining 95 month-long, 1-hour resolution time series of a volumetric hot water consumption at different households. In addition, the aggregate dataset was also generated for comparison reasons, containing the average hot water consumption from 95 dwellings. The separate consumption profiles were normalised using the standard deviation before taking the arithmetic mean.

4.3.3.2 Forecasting models

It is a general practice to compare model performance with standard simple benchmark models [DFY11]. The authors have chosen mean, simple and seasonal naive benchmark models to be compared to the models developed in this paper. The mean forecasting model computes the values of the horizon by taking the arithmetic average of past values. The simple naive model basically assumes that every future forecast is equal to the most recent value observed. These two models have been chosen as a baseline for forecasting. Since the data are exclusively periodic due to the fact that people tend to have habits, there should be seasonality in the benchmark model. For this reason, the authors have decided to use the seasonal naive model, which computes forecasts by observing the value at the same time in the previous season [HK06]. In this paper, there are two seasonal periods considered: a day-long period and a week-long period.

Figure 4.12 illustrates the performance of benchmark models for single house hot water consumption. It can be seen that both the mean and naive models do not perform well for 24 h ahead forecasting. A better performance is observed from seasonal naive models, and this suggests that seasonality plays a key role.

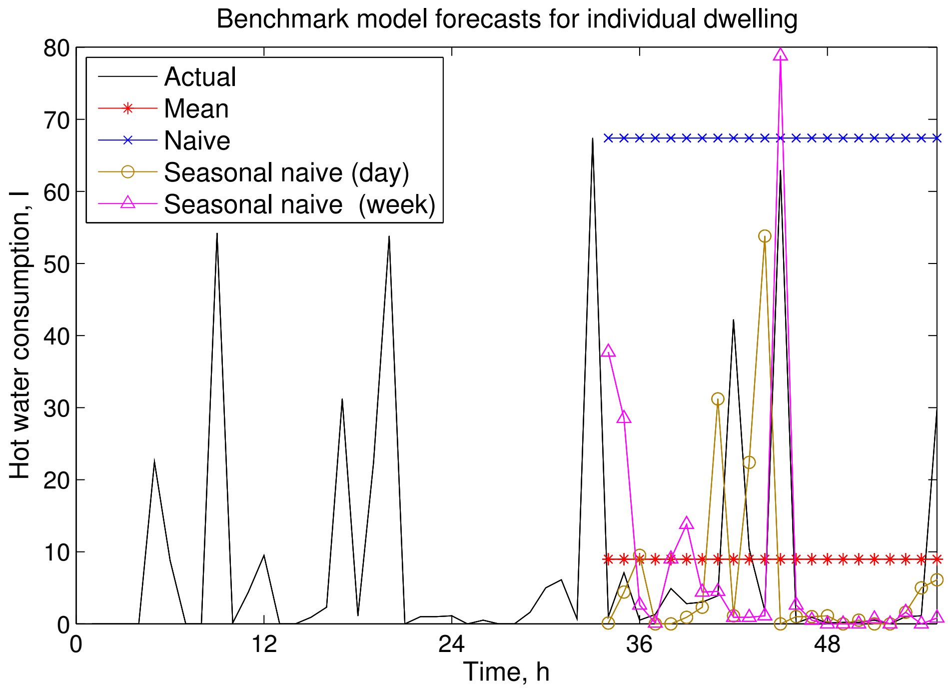

Fig. 4.12 Examplar enchmark model forecasts for individual dwelling.

Figure 4.13 shows an example forecast for total hot water consumption. Since this time series involves information from many consumers, the aggregate profile is more stable and repetitive compared to profiles from individual dwellings, thus seasonal naive models perform reasonably well. In this paper, all other models will be compared to the seasonal naive (daily) model. Both individual and aggregate data were fitted to a number of models: exponential smoothing (ETS), seasonal autoregressive integrated moving average (ARIMA), seasonal decomposition of time series by Loess model (STL) and a combination of them.

The exponential smoothing state space models are fitted using the R software environment. It offers an automated model selection and fitting tool. The notation in this paper follows the ETS() function from R. The three parameters are the error, trend and seasonal components and can be additive (A), multiplicative (M) or none (N). The best performing model parameters are chosen using the information criterion. The combinations of these correspond to different models, but this is out of the scope of this paper

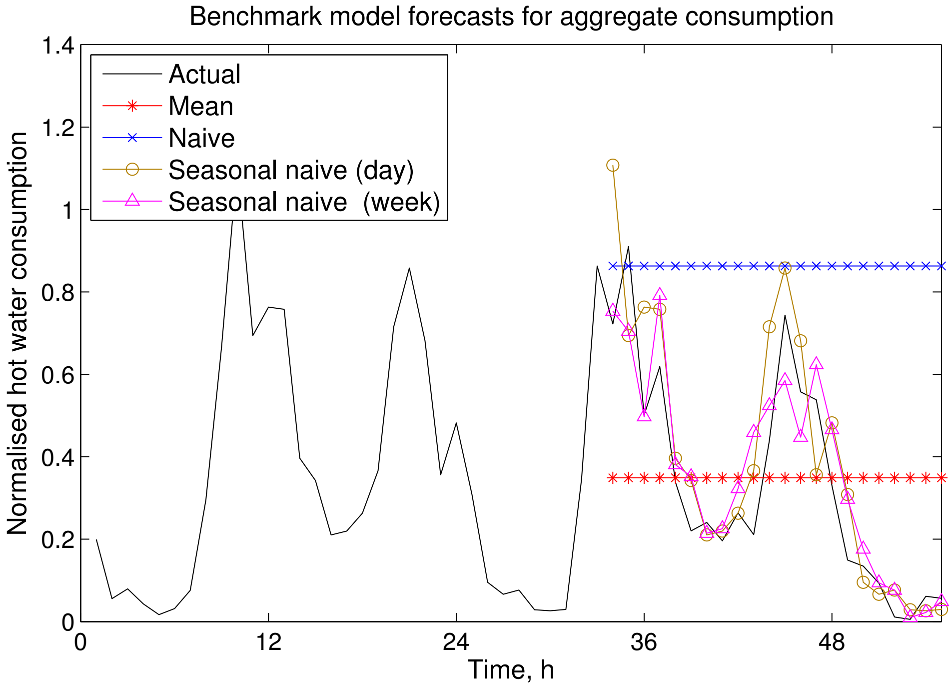

Fig. 4.13 Exemplar benchmark model forecasts for aggregate hot water consumption.

[Hyn15, HK06]. The results showed that for individual forecasts, the best performing model was ETS(A,N,A) for every dwelling. For the aggregate consumption case, the best results were shown by the ETS(M,N,M) model.

The seasonal autoregressive integrated moving average is a well-established modelling technique, better known as the Box-Jenkins methodology. A series of models were fitted using the ARIMA() function in R software [Hyn15]. It chooses the parameters for the best fitting model according to either the Akaike information criterion (AIC), the corrected Akaike information criterion (AICc) or the Bayesian information criterion (BIC). These parameters are:

- p, the number of autoregressive terms;
- d, the number of non-seasonal differences needed for stationarity;
- q, the number of lagged forecast errors in the prediction equation;
- P, the seasonal autoregressive terms;
- D, the number of seasonal differences;
- Q, the number of seasonal lagged forecast errors in the prediction equation.

Model orders were not fixed; thus, different dwellings were assigned to the best performing ARIMA models. The model order distribution is then calculated and compared to the parameters of the aggregate time series model.

The seasonal decomposition of time series split the time series into seasonal, trend and irregular parts by Loess. At first, the seasonality is removed using Loess by smoothing the seasonal sub-series. The remainder is then smoothened to find the trend. A combination of STL and ETS or ARIMA was also used. The time series were first decomposed, then the forecasting model was fitted to the seasonally adjusted data, and finally, the datasets were re-seasonalised.

The main factors affecting the accuracy of the forecast are the data aggregation level, the forecasting horizon and the time series sparsity. In this paper, both individual and aggregate demand profiles are forecasted using 10 different models. It should be noted that single house hourly water usage time series are very sparse. The aggregate data, on the other hand, contain far less zeros. It is expected to get much better forecasts for average consumption profiles compared to individual houses. The forecasting horizon is up to 24 h for all data series.

4.3.3.3 Performance Evaluation

There are many possible ways to measure how well the forecasting models perform. The most general practice is to compare mean absolute error (MAE) or root mean square error (RMSE), which are scale-dependent measures. Since different dwellings accommodate a different number of people and their water usage habits vary, absolute measures need to be either normalised or, alternatively, relative measures need to be taken. To normalise MAE and RMSE, a standard deviation (SD) of measurements was used. As a result, normalised MAE and normalised RMSE could be calculated as follows:

$$nMAE = \frac{mean(|e_t|)}{sd(y_t)} \tag{4.2}$$

$$nRMSE = \frac{\sqrt{mean(e_t^2)}}{sd(y_t)} \tag{4.3}$$

where e_t is the forecast error and y_t is the target value. Functions $mean()$ and $sd()$ are the arithmetic average and the standard deviation, respectively.

Mean absolute percentage error (MAPE) could be another possible choice for performance evaluation; however, hot water consumption time series are very sparse, and errors are compared to zero values, making the calculations unstable. This makes MAPE unsuitable in this application. The method proposed by Hyndman and Koehler in [HK06] suggests comparing the errors given by the forecasting models to the errors from seasonal naive benchmark models to overcome this issue. The scaled errors would then be defined as:

$$q_t = \frac{e_t}{\frac{1}{T-s}\sum_{i=s+1}^{T} |y_i - y_{i-s}|} \tag{4.4}$$

where q_t is the scaled error, e_t is the forecast error, T is the time series length, s is the season parameter and y is the set of target values. The seasonal parameter is equal to 24 h in this comparison. The mean absolute scaled error (MASE) is defined by Equation (4.5):

$$MASE = mean(|q_t|) \tag{4.5}$$

In addition, the authors of this paper have measured the regression value R as another way of assessing the model's performance. It is the regression value of the one-step-ahead forecast *versus* the target value. All other performance measures were also calculated using one-step-ahead forecasts from test datasets.

4.3.4 Time Series Analysis

This section involves the preliminary analysis of the time series of DHW usage.

4.3.4.1 Time Series Stationarity

This section determines whether the original time series need any nonlinear transformation to become stationary. For that, five different tests were used [Ham94]:

- Augmented Dickey-Fuller test (ADF);
- Kwiatkowski-Phillips-Schmidt-Shin test (KPSS);
- Leybourne-McCab stationarity test (LMC);
- Philip-Perron test (PP);
- Canova-Hansen test (CH).

Data for every dwelling were tested separately using the MATLAB and R software environments. A decision about whether the particular time series is stationary or not was made.

Table 4.2 shows the percentage of stationary data using the corresponding test and differencing level. Firstly, the tests were run on the initial data, and then, the data were differenced using first order differentiating. Finally, these were seasonally differenced (weekly season), and the first difference of seasonal difference was calculated. The

KPSS and LMC tests show a relatively similar outcome, whereas the ADF and PP tests approved all data series to be stationary. The CH seasonal unit root test rejected 36% of dwellings, meaning 64% of them have seasonal unit roots. The same tests were executed on the aggregate dataset. Only KPSS and CH tests required first order differentiation and first order seasonal differentiating correspondingly.

Table 4.2 Stationarity test results.

Stationarity test	Initial	Non-seasonal diffferencing 1st order	Seasonal differencing	
			Seasonal	1st diff of seasonal
ADF [1]	100%	100%	100%	100%
KPSS [2]	12%	100%	83%	100%
LMC [3]	18%	87%	100%	100%
PP [4]	100%	100%	100%	100%
CH [5]	36%	-	100%	-

[1] Augmented Dickey-Fuller; [2] Kwiatkowski-Phillips-Schmidt-Shin; [3] Leybourne-McCab; [4] Philip-Perron; [5] Canova-Hansen.

Based on the results summarised in Table 4.2, it can be concluded that a level of differencing is inevitable. Nearly all data become stationary when the first order differential is taken. This makes the ARIMA(p,1,q)×(P,0,Q) model a good candidate. As a rule of thumb, no more than two orders of differentiation should be used. In practice, it is hard to decide whether time series are stationary or non-stationary, so a "second order" or "weak" stationarity is used.

Autocorrelation (ACF) and partial autocorrelation functions (PACF) were used to visually examine both individual dwelling time series and aggregate time series of volumetric water consumption. ACF and PACF plots are shown in Figures 4.14 and 4.15. The blue lines represent the upper and lower confidence bounds. The slow decay of ACF suggests that there is slight non-stationarity in the initial data. These plots also demonstrate that data are highly repetitive and have two seasons, daily and weekly (as there are spikes at the 24th and the 168th hour lag in both PACFs).

4.3.4.2 Seasonality Analysis

As mentioned above, by looking at the hot water usage time plots, autocorrelation functions, as well as the partial autocorrelation functions, it is clear that there is daily and weekly seasonality involved.

Seasonal factors are calculated by taking the average consumption of the same hours from different weeks (seasons) and then normalising it to mean consumption. Figure 4.16

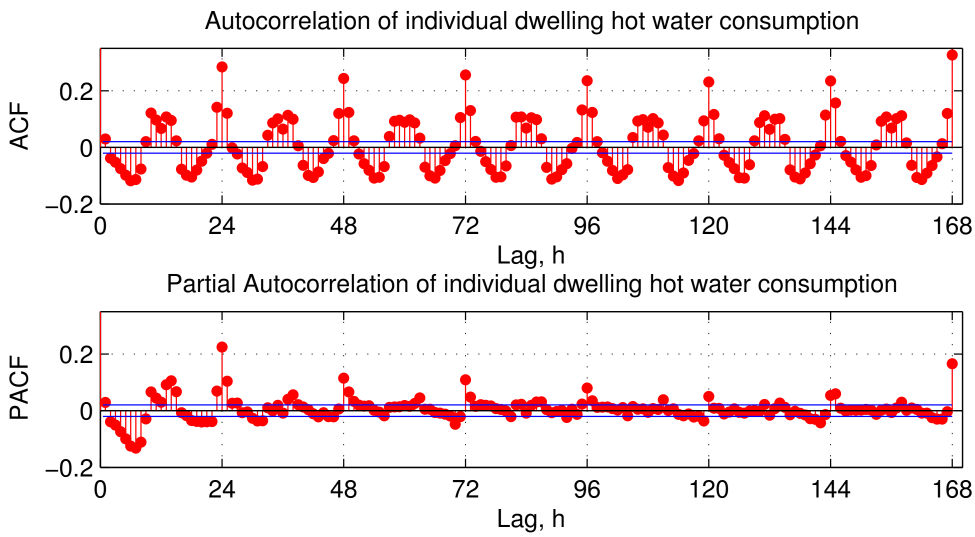

Fig. 4.14 Autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of hot water consumption at the exemplar dwelling. Blue lines show confidence bounds.

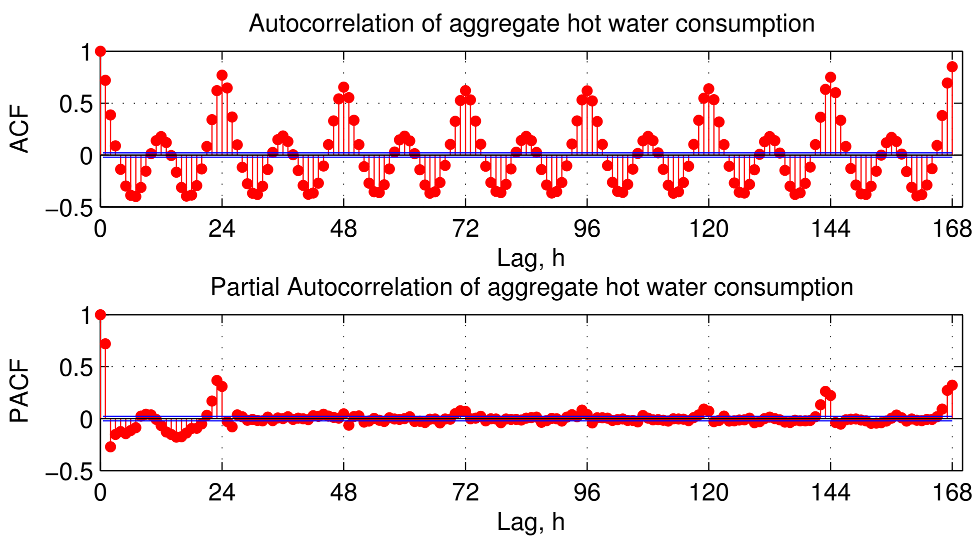

Fig. 4.15 ACF and PACF of aggregate hot water consumption. Blue lines show confidence bounds.

shows the overlaid daily seasonal plot of average seasonal factors. It can be observed that there is very strict repetitiveness from Monday to Friday. The weekend is slightly lagging, supposedly because people tend to start their day later during the non-working days. It can also be seen that the hot water consumption profile is generally flat during the weekend. In addition, the Sunday evening peak is highest, most likely due to certain household activities before the start of a new week. Another interesting observation is that around 9 a.m. on Mondays and Fridays, there is an increased water usage compared to other working days. Note that this increase coincides with the weekend morning peak, thus the assumption can be made that it is caused by long weekends.

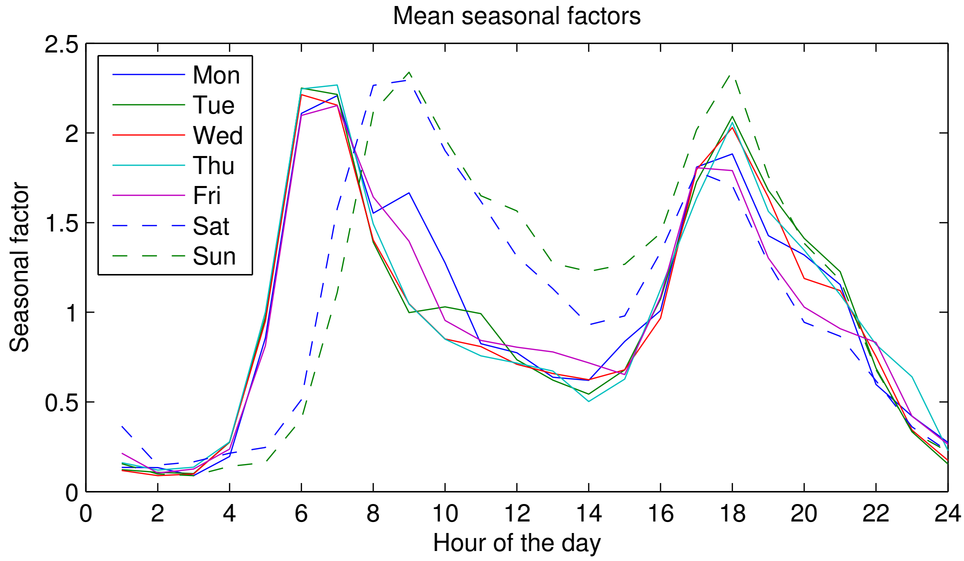

Fig. 4.16 Seasonal plot of mean seasonal factors.

Figure 4.17 shows how seasonal factors are distributed in all houses. The boxplot reveals that even though the average seasonal factors are closely matched for consecutive days, there is a wide variety of seasonal patterns between dwellings. This might be due to the fact that occupants from different dwellings have different hot water consumption habits, which might be beneficial for the end goal of demand-side management.

Forecasting models analysed in this paper can handle seasonality, thus it is not necessary to de-seasonalise the data beforehand. Basically, “STL and ETS” and “STL and ARIMA” do exactly the same process: they first de-seasonalise the data, apply the forecasting method and then re-seasonalise the data.

4.3.5 Results

The forecasting results of hot water usage in individual dwellings are positive and promising. Every forecasting method outperformed the chosen benchmark models.

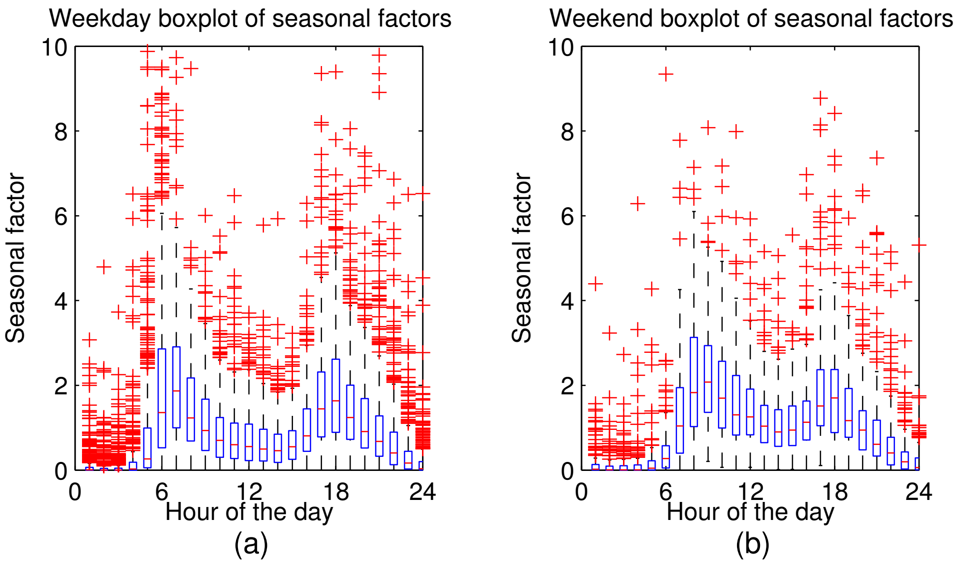

Fig. 4.17 Hourly boxplots of seasonal factors from different dwellings. (**a**) Weekdays only; (**b**) Weekends only.

Table 4.3 and Figure 4.18 summarise how well the models performed by showing the average performance measures from the best fitting model for every dwelling. For a particular dwelling, the best-performing models were chosen by adjusting the parameters, for example *p*, *d* and *q* values in the ARIMA model were chosen using the Akaike or the Bayesian information criterion [Hyn15]. A standard deviation is also presented showing how much performance measures differ between houses. It can be seen that seasonal decomposition in conjunction with exponential smoothing (STL and ETS(A,N,N)) and ARIMA (STL and ARIMA(*p*,*d*,*q*)) perform the best. On average, they perform more than 30% better than the seasonal naive benchmark model.

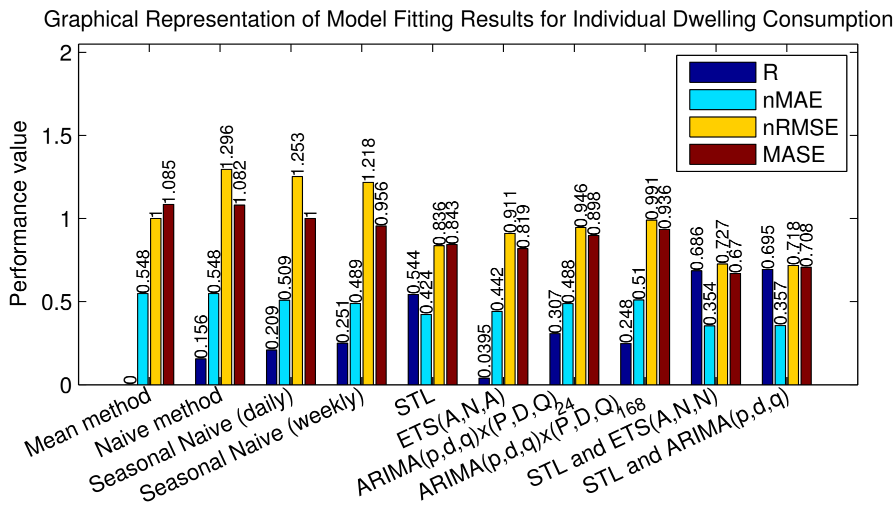

Fig. 4.18 Graphical representation of Table 4.3.

Table 4.3 Model fitting results for individual dwelling consumption. MASE, mean absolute scaled error; STL, seasonal decomposition of time series by Loess; ETS, exponential smoothing.

Method	Performance measures			
	R (SD)	nMAE (SD)	nRMSE (SD)	MASE (SD)
Mean method	0.000 (0.000)	0.548 (0.097)	1.000 (0.000)	1.085 (0.145)
Naïve method	0.156 (0.084)	0.548 (0.109)	1.296 (0.067)	1.082 (0.142)
Seasonal naïve (daily)	0.209 (0.117)	0.509 (0.095)	1.253 (0.098)	1.000 (0.000)
Seasonal naïve (weekly)	0.251 (0.126)	0.489 (0.106)	1.218 (0.109)	0.956 (0.073)
STL	0.544 (0.072)	0.424 (0.056)	0.836 (0.053)	0.843 (0.061)
ETS(A,N,A)	0.395 (0.112)	0.442 (0.070)	0.911 (0.055)	0.819 (0.096)
ARIMA$(p,d,q)\times(P,D,Q)_{24}$	0.307 (0.112)	0.488 (0.081)	0.946 (0.039)	0.898 (0.067)
ARIMA$(p,d,q)\times(P,D,Q)_{168}$	0.248 (0.113)	0.510 (0.092)	0.991 (0.092)	0.936 (0.065)
STL and ETS(A,N,N)	0.686 (0.056)	**0.354 (0.052)**	0.727 (0.057)	**0.670 (0.041)**
STL and ARIMA(p,d,q)	**0.695 (0.054)**	0.357 (0.053)	**0.718 (0.056)**	0.708 (0.045)

Table 4.4 shows the parameter distributions of the best fitting seasonal and non-seasonal ARIMA models. The first order parameter is the most common. Model selection resulted in about 60% of the time series requiring first order differentiating in order to be stationary. This complies with the stationarity test results that were previously conducted. On the other hand, seasonal differencing is not required according to stationarity tests and model fitting results (none of the best fitting models required seasonal differencing).

Two exemplar forecasting cases have been plotted. Figures 4.19 and 4.20 demonstrate 24 h ahead forecast together with 80% and 95% confidence intervals.

Residual analysis plots for exemplar cases can be found in Figures 4.21 and 4.22. They depict the distribution of errors using the Q-Q plot by plotting the distribution of residual errors *versus* the normal distribution. The bottom part of the figure shows the residual error ACF and PACF plots.

Finally, Table 4.5 and Figure 4.23 show the performance results for aggregate consumption forecasts. Both individual and aggregate consumption forecasts were computed using similar models so that the result could be compared easily.

4.3.6 Discussion

By comparing Tables 4.3 and 4.5, it can be seen that the aggregate consumption profile is more predictable than individual consumption profiles. The best MASE for aggregate data is 0.573 compared to the MASE of 0.670 for separate house forecast. Normalised RMSE is about two times less for mean consumption data, where approximately 30%

Table 4.4 Seasonal ARIMA model orders.

Method	**Parameters (orders)**					
	p	***d***	***q***	***P***	***D***	***Q***
ARIMA$(p, d, q)\times(P, D, Q)_{24}$	0 – 22 % 1 – 40 % 2 – 30 % 3 – 7 % 4 – 1 %	0 – 40 % 1 – 60 %	0 – 15 % 1 – 36 % 2 – 32 % 3 – 10 % 4 – 7 %	0 – 31 % 1 – 41 % 2 – 28 %	0 – 100 %	0 – 21 % 1 – 21 % 2 – 58 %
ARIMA$(p, d, q)\times(P, D, Q)_{168}$	0 – 29 % 1 – 34 % 2 – 28 % 3 – 7 % 4 – 2 %	0 – 40 % 1 – 60 %	0 – 29 % 1 – 37 % 2 – 24 % 3 – 9 % 4 – 1 %	0 – 51 % 1 – 39 % 2 – 10 %	0 – 100 %	0 – 49 % 1 – 51 %
STL and ARIMA(p,d,q)	0 – 8 % 1 – 36 % 2 – 30 % 3 – 14 % 4 – 12 %	0 – 37 % 1 – 63 %	0 – 10 % 1 – 25 % 2 – 33 % 3 – 20 % 4 – 12 %	N/A	N/A	N/A

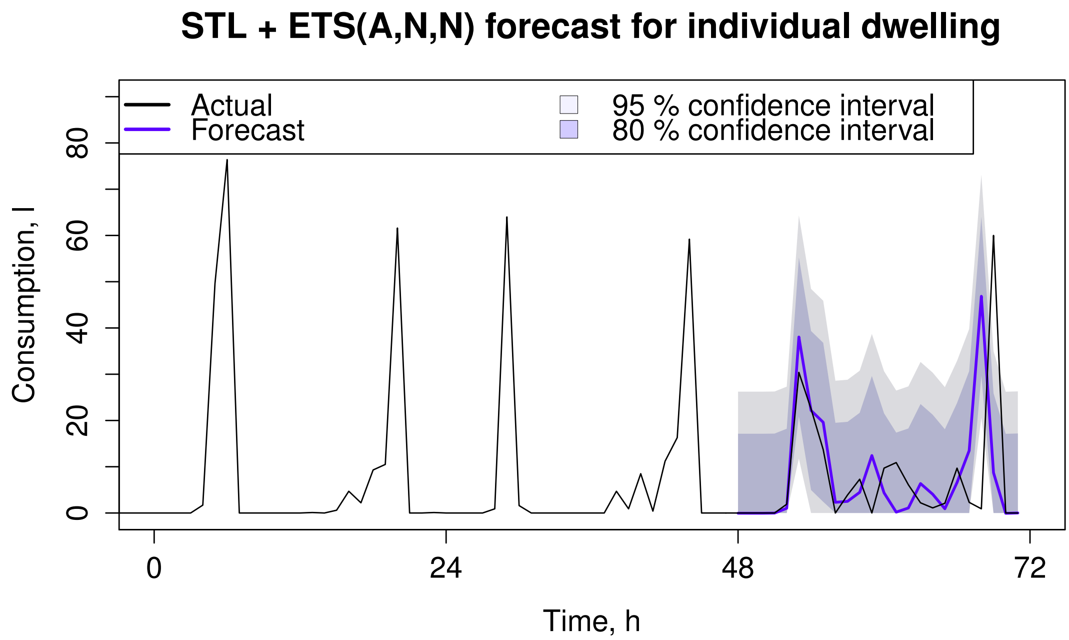

Fig. 4.19 Best performing method for non-aggregate time series.

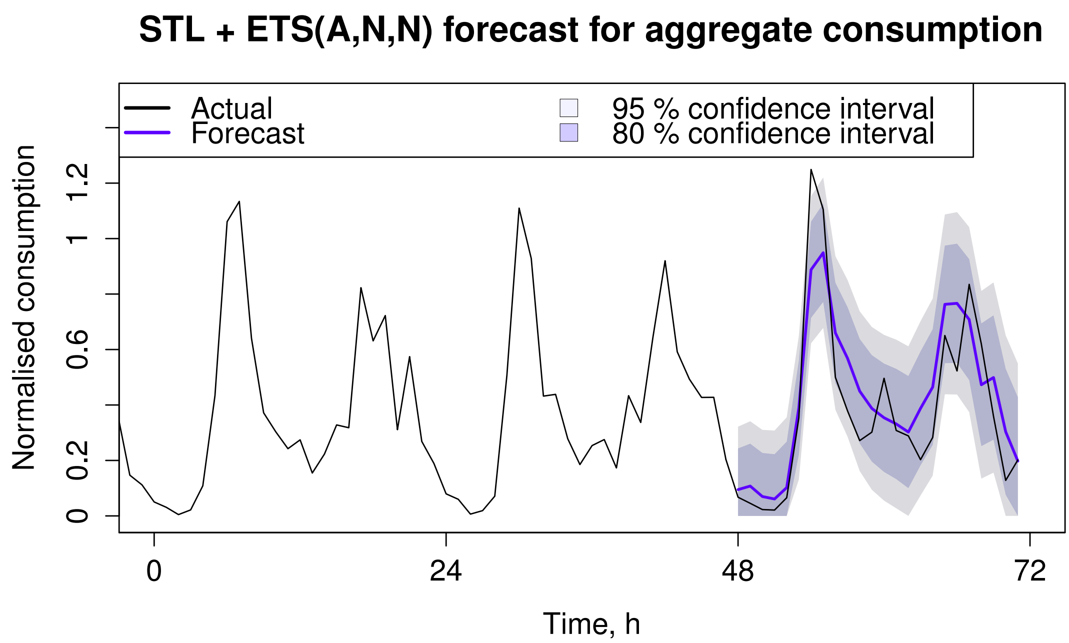

Fig. 4.20 Best performing method for aggregate time series.

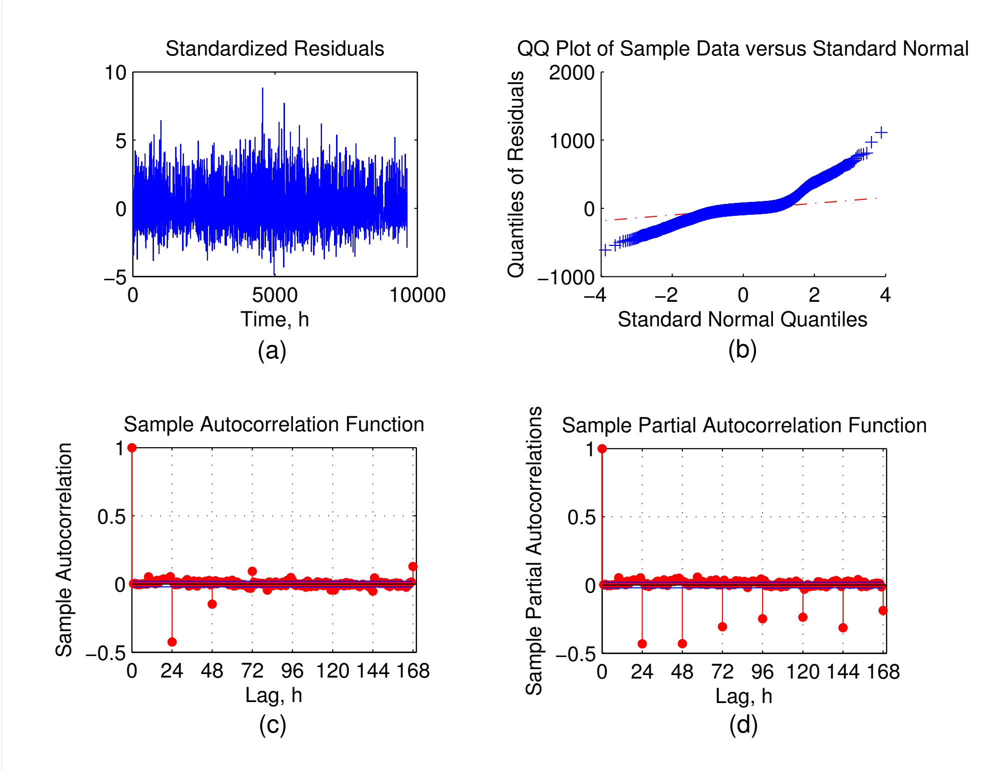

Fig. 4.21 Residual analysis for the single dwelling consumption forecast. (**a**) Standardised residuals; (**b**) Q-Q plot of residuals; (**c**) ACF of residuals; (**d**) PACF of residuals.

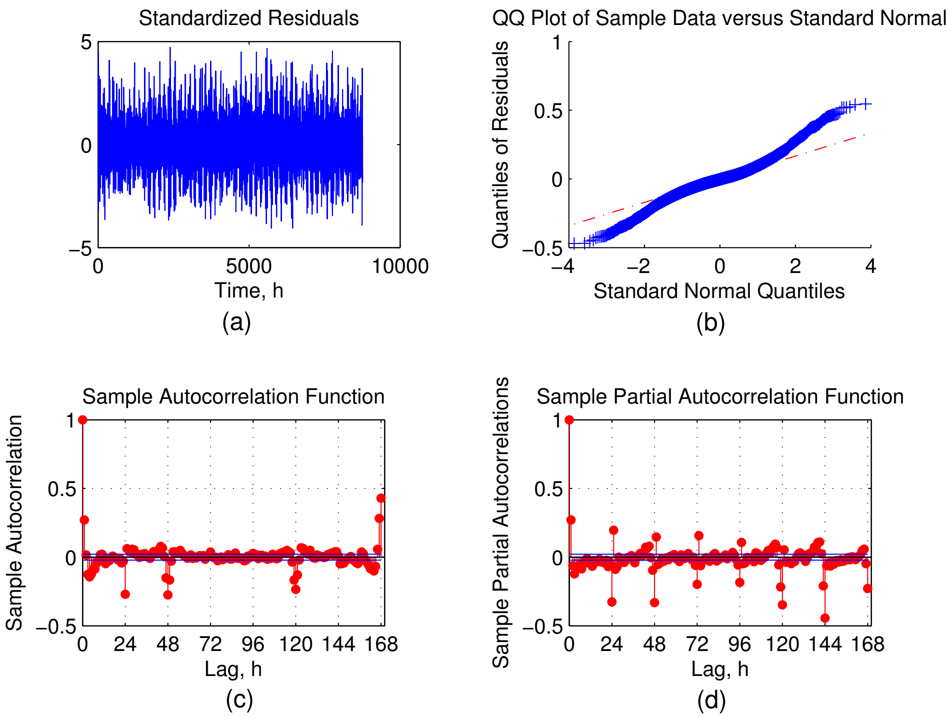

Fig. 4.22 Residual analysis for aggregate consumption forecast. (**a**) Standardised residuals; (**b**) Q-Q plot of residuals; (**c**) ACF of residuals; (**d**) PACF of residuals.

Table 4.5 Model fitting results for average consumption.

Method	Performance measures			
	R	nMAE	nRMSE	MASE
Mean method	0.000	0.823	1.000	1.799
Naïve method	0.719	0.535	0.750	1.170
Seasonal naïve (daily)	0.772	0.457	0.675	1.000
Seasonal naïve (weekly)	0.865	0.366	0.520	0.801
STL	0.863	0.354	0.506	0.775
ETS(M,N,M)	0.811	0.412	0.588	0.771
ARIMA(1,1,1) $\times$ (1,0,2)$_{24}$	0.871	0.351	0.491	0.656
ARIMA(1,1,2) $\times$ (1,0,0)$_{168}$	0.872	0.357	0.490	0.667
STL and ETS(A,N,N)	0.919	0.281	0.394	0.614
STL and ARIMA(3,1,1)	**0.932**	**0.262**	**0.363**	**0.573**

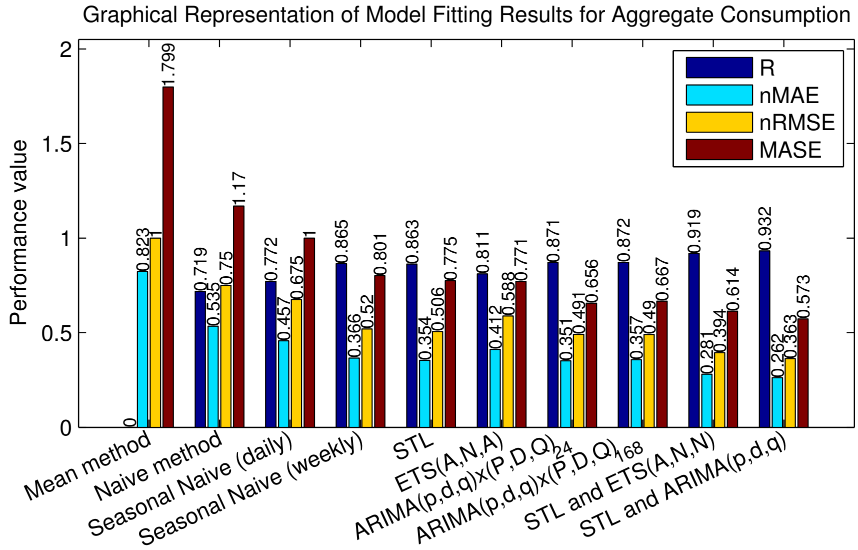

Fig. 4.23 Graphical representation of Table 4.5.

improvement is seen on the R value and normalised MAE. As mentioned in Section 4.3.3.3, the scale of consumption profiles differs between dwellings due to different numbers of occupants and water usage habits, so it is best to measure performance by looking at relative figures. Nevertheless, mean absolute errors were calculated for all individual forecasting performances and are in a range of 4.4 to 6.9 L/h. The best performing model (STL and ETS(A,N,N)) corresponds to an error of 4.4 L/h.

Consumption peaks in individual dwellings are very high and narrow (on some occasions, consumption changes from zero to 100 L and back to zero in three consecutive hours), meaning the consumption is very concentrated in time. When the repetitive water usage is in between two consecutive hours, it is very hard to predict at which hour the peak will appear. Due to this extreme behaviour and sparse time series, forecasting becomes very time sensitive, *i.e.*, if the forecast is off by one single time step, the performance measures drop dramatically, and the confidence intervals increase.

This problem worsens for higher resolution forecasts. The authors found that a resolution of one hour gives the best trade-off between forecast accuracy and the need to have sub-hour information. Various DR programs are designed to respond for up to sub-minute power fluctuations. It must be noted that although this paper describes hourly hot water consumption forecasts, the potential demand response program might be of a higher resolution, which is mainly limited by the communication channel parameters. The hot water consumption forecasts could potentially be used for deciding whether a particular water heater is capable of responding to a particular period of time.

The confidence intervals show the probability of the forecast to be accurate, *i.e.*, wider intervals mean less confident forecasts. It can be seen that individual dwelling consumption forecasts produce wider confidence intervals than aggregate consumption forecasts, meaning it is harder to confidently predict individual hot water usage as opposed to total collaborative usage. The ability to predict DHW usage at the individual house level is the key to successful DSM program implementation. Although the confidence intervals suggest that there could always be a fair amount of water usage, the model accurately predicts the time of high demand periods. On the other hand, the forecast for mean consumption is more accurate compared to individual consumption, and the confidence intervals are narrower, due to consumer diversity.

The Q-Q plot demonstrates that the residual errors follow a normal distribution quite well, which means that residuals are mostly white noise and the model incorporates enough information to predict ahead. There is a fair amount of error autocorrelation at multiples of 24-h lags in Figure 4.21, bottom. This could be explained by closely examining error time plots and is related to time series being sparse. There is a clear pattern of a high and a low probability for errors. During the night, the consumption reduces to the minimum, and the resulting errors are also small. The opposite happens during the peak consumption. This behaviour makes the error autocorrelation inevitable at multiples of 24.

4.3.7 Conclusions

In conclusion, the increased global energy consumption and the expansion of intermittent renewable generation require new electricity balancing tools. The DSM technologies have huge potential to use distributed water heaters as energy shifting devices for solving this energy balancing problem.

The main goal of this paper was to research the possibility of forecasting hot water volumetric consumption at an individual dwelling level. DSM programs that incorporate forecasts tailored to individual houses can respond to energy surplus or shortage more reliably and, hence, perform better.

This paper also analysed hot water consumption profiles for 95 individual dwellings and aggregate information. Strong daily and weekly usage patterns were detected; hence, seasonal forecasting models were used. The forecasting techniques were applied to acquire 24 h ahead forecasts using estimated exponential smoothing, ARIMA and seasonal decomposition models. The results show that chosen prediction methods could be potentially used for DSM applications to control hot water consumption possibly without compromising user's comfort. The best performing models were discovered to be "STL and ETS(A,N,N)" and "STL and ARIMA(p,d,q)".

Future work might include taking into account time of the year (yearly seasonality), total number of occupants, as well as the number of children, weather information and information from the user (set of holiday dates). Furthermore, as future work, these forecasts could be tested in the context of DSM and DR.

Acknowledgement

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Chapter 5

Distributed Energy Storage using Residential Hot Water Heaters

5.1 Renewable Energy Integration using Residential Sector

The previous chapters demonstrated the need for ancillary services to help integrate intermittent renewable energy, i.e. low predictability wind power. Chapter 4 demonstrates the design of various different forecasting models that can be used to raise awareness of energy balance within thermal storage capable devices. The best performing forecasting method is used in this chapter. The methodology to create smart residential hot water heaters using thermal usage prediction is also described in this chapter. This is the residential approach to energy balancing problem, which is one of two discussed in this thesis. The other approach is discussed in the next chapter.

5.2 Distributed Energy Storage using Residential Hot Water Heaters

Distributed Energy Storage using Residential Hot Water Heaters

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Abstract

This paper proposes and analyses a new demand response technique for renewable energy regulation using smart hot water heaters that forecast water consumption at an individual dwelling level. Distributed thermal energy storage has many advantages, including high overall efficiency, use of existing infrastructure and a distributed nature. In addition, the use of a smart thermostatic controller enables the prediction of required water amounts and keeps temperatures at a level that minimises user discomfort while reacting to variations in the electricity network. Three cases are compared in this paper, normal operation, operation with demand response and operation following the proposed demand response mechanism that uses consumption forecasts. The results show that this technique can produce both up and down regulation, as well as increase water heater efficiency. When controlling water heaters without consumption forecast, the users experience discomfort in the form of hot water shortage, but after the full technique is applied, the shortage level drops to nearly the starting point. The amount of regulation power from a single dwelling is also discussed in this paper.

5.2.1 Introduction

A distinctive characteristic of the electric power sector is that the amount of generated electricity has to be equal to the amount of consumed electricity at every single instance [KBL94]. Unfortunately, there are peaks and valleys of total consumed electric energy, which do not always coincide with available generation patterns. People tend to have habits, including morning and evening rituals, that require large amounts of energy; thus, peaks are created. In addition, the generation side failures or other disruptions necessitate costly regulation ancillary services to match the demand with supply [BGAG14]. As a result, national transmission system operators (NTSO) constantly monitor the system and adjust the generation to meet the demand using ancillary services.

The increase of renewable energy generation attempts to solve problems associated with the conventional generation (such as emissions of greenhouse gasses), but creates power balancing issues [GG14]. Renewable energy is inherently intermittent and hard to control. As a result, its output is highly variable, and the electricity balancing problem becomes even more difficult [LLMS15]. Many researchers agree that wind generation introduces unprecedented amounts of uncertainty. The importance of demand side management (DSM) for long-term sustainable energy use in high renewable energy penetration areas is discussed in [PSF12]. The power reserve limit needs to be increased when adding wind power to the system; otherwise, reliability is sacrificed [DO05]. It also makes unit commitment and economic dispatch problems more complicated, which are assessed in [WBB$^+$11]. Studies show that in some countries in 2020, up to 13% of trade periods will require wind curtailment [FFC$^+$11], indicating high wind generation uncertainty. According to [BS07], a forecasting horizon further than 4 h requires weather information to acquire better accuracy; therefore, wind generation forecasting results are highly dependant on the climate of a location. Wind power forecast uncertainty using probabilistic forecasting is described in [MB11], and in [DO05], the authors demonstrate the standard deviation of error of day-ahead forecast to be 0.22 per MW of installed power in Ireland. Up to now, traditional pumped hydro storage facilities primarily have served as part of the backup power, but this cannot meet the high rate of output change from renewable power plants [BGAG14, GBGA16]. In addition, centralised backup power requires energy to be transmitted back and forth; thus, transmission losses have to be accounted for, as well.

Energy storage fundamentally improves the way electricity is generated, transmitted and consumed [DO09]. It allows the decoupling of generation from consumption to a certain level [CCY$^+$09]. Hence, more storage on the grid significantly reduces generation dependency on the consumption. In addition, storage devices would also help during power outages, caused by equipment failures/faults or accidents. Moreover, the transmission and distribution grid has capacity limits, which might be exceeded during peak electricity usage. Energy storage would also help the grid to smooth energy transportation, increase electricity throughput to its maximum and increase load factor [DS09]. This would significantly lower the infrastructure costs as the transmission and distribution equipment has to be designed for peak demand, which occurs less than 5% of the time [GG14]. Furthermore, it enables the potential of running generating units at their maximum efficiency point, thus eventually decreasing generation costs.

DSM is a broad set of means to alter the time and magnitude of end user's electricity consumption, one of which is load shifting. Load shifting techniques require storage capabilities, such as thermal storage devices. Water heaters are perfect candidates as demand responsive devices. In general, water heating accounts for 17% of all residential energy use in the United States [HK09]. Resistive hot water heaters are common in residential houses and make up 40% of all hot water heaters in the U.S. [HK09] and 12%–20% in the U.K. (depending on the season) [NA99], meaning the infrastructure is already established. They exhibit good thermal storage properties [AATM14], possess high nominal power ratings and large thermal buffer capacities, as well as a fast response to load change [PLC10, Eri09, VDGJ12]. Water has relatively high specific heat, which allows it to store large amounts of energy. Furthermore, in resistive water heaters, electricity is transferred to useful heat at 100% efficiency, and energy is lost only due to heat transfer through insulating walls.

Various hot water heater control techniques can be seen in the literature. The load commitment technique using real-time and forecasted pricing of electricity was researched by scientists in [DL11], whereas other researchers discussed a technique using timer switches for hot water load management [Ati13]. Kepplinger *et al.* [KHP15] demonstrate optimal control of hot water heaters using linear optimisation. The aggregate regulation service for renewable energy using thermally-stratified water heater model was analysed by Kondoh *et al.* [KLH11]. The model is designed to have two heating elements, but only one is assigned for regulation services; thus, in essence, only one half of the thermal capacity is used for demand response (DR), and the other half is used to guarantee end users' comfort. Furthermore, there is an ongoing work to increase the efficiency of water heaters using baffles based on computational fluid dynamics [SK13]. Electric water heating control techniques to integrate wind power are compared by Fitzgerald *et al.* [FFM12], whereas Finn *et al.* examines the impact of load scheduling on the adaption of wind generation [FFC$^+$11]. Another study on the load balancing technique using an aggregate heating, ventilation and air conditioning (HVAC) system is presented by Lu in [Lu12].

The widespread acceptance of DSM programs relies on minimal impact to the comfort of users [PLC10]. This paper proposes a new strategy to control residential hot water heaters with minimal change in users' comfort levels. In this research, the focus was to eliminate the imbalance caused by wind power plants, although this technique is not limited to solving problems associated with renewable energy generation. It could help in cases of generation faults or it could be used as an ancillary service or by energy traders to profit from the fluctuating real-time price of electricity.

5.2.2 System Description and Methodology

This section describes the general methodology and techniques used in the design of the residential water heater-based distributed energy storage system. It also describes the data preparation, model design, evaluation and comparison of different scenarios.

5.2.2.1 Thermal Water Heater Model

The dynamic thermal water heater model was derived based on open system energy balance [DL11, KHP15, NJPH07]. The amount of energy consumed by the electric heating element is added to the model as an input, whereas the outputs are (1) energy consumed by hot water usage and (2) thermal energy losses due to imperfect thermal insulation. The amount of water drawn from the tank is based on measurement data collected from individual dwellings [ene08]. The temperature of the inlet water and the specific heat of water at normal temperature and pressure (NTP) conditions were also taken into account. Thermal losses are calculated based on the temperature difference between water and ambient temperature and thermal conductivity. The model is fully mixed, unstratified, meaning water temperature is the same throughout the tank. The effect of temperature variation at the output is compensated by demanding more water in case the temperature is cooler than the setpoint and demanding less if the temperature is higher. According to [COS11], the fully-mixed model shows increased thermal energy losses, so heat transfer coefficients were adjusted to compensate for this. Figure 5.1 graphically depicts the energy conservation of the system.

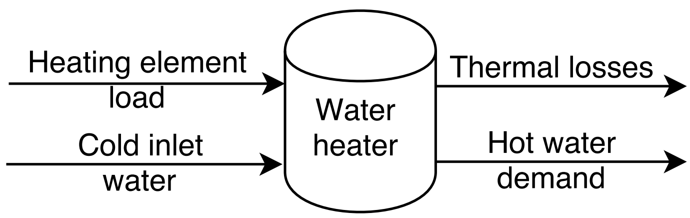

Fig. 5.1 Thermal water heater diagram.

The mathematical model of the thermal system could be described as [DL11]:

$$Q_{t+1} = Q_t + \Delta t S_{0/1} K_{\mathrm{HE}} + C_{\mathrm{W}} D_t (T_{\mathrm{WH}} - T_{\mathrm{in}}) + \Delta t k (T_{\mathrm{WH}} - T_{\mathrm{amb}}) \tag{5.1}$$

$$T_{\mathrm{WH}} = \frac{Q_t}{m C_W} \tag{5.2}$$

$$40\ ^{\circ}C < T_{\mathrm{WH}} < 90\ ^{\circ}C \tag{5.3}$$

where Q_t (J) is the thermal energy stored in the water tank (integrator); Δt (s) is the time step length; $S_{0/1}$ is the on/off state of the heating element (WH control); K_{HE} (W) is the heating element rating; C_{W} (J/kg°C) is the specific heat of water; m (kg) is the mass of water in a single device; D_t (kg) is the demand of hot water at time t; k (J/s°C) is the heat transfer coefficient for particular device and T_{in} (°C), T_{WH} (°C) and T_{amb} (°C) are inlet cold water, hot water and ambient temperatures respectively. The model was then implemented in the Matlab Simulink software environment which can be seen in Figure 5.2.

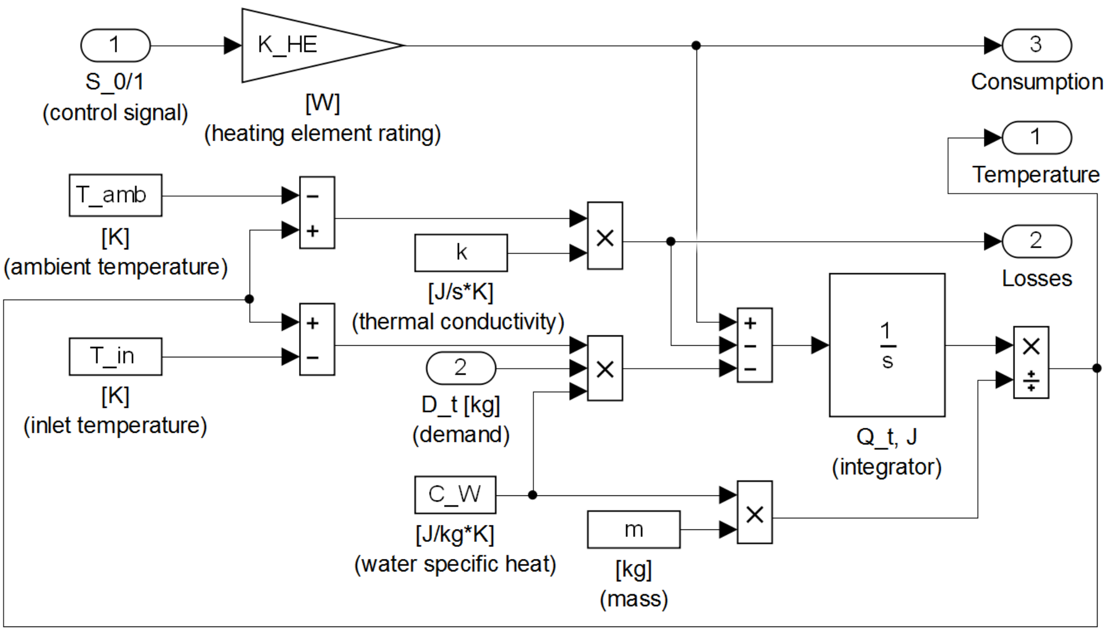

Fig. 5.2 Thermal water heater block diagram model.

5.2.2.2 Smart Hot Water Heater Controller

The smart hot water heater controller in the proposed system controls the heating element according to the consumption forecasts and the signal sent from the smart grid. The controller is capable of locally forecasting hot water consumption of a particular dwelling. It contains an artificial neural network (ANN) model, which is trained based on the past hot water consumption information. The ANN model can compute short-term hot water usage forecasts tailored for the particular house. The controller also contains thermal model, so based on the consumption forecast, it can compute water temperature for the next 12 h period. It also receives a signal from the grid showing the requested duty cycle of the heating element. The signal is percentage-wise, where 0% means that the grid experiences a shortage of electricity, thus requesting to turn the heating element off, and 100% means a surplus of energy in the grid. The overall operation of the controller is described in Section 5.2.2.5.

The ANN model that is used in the proposed system is based on the results from previous research [GG15a, GG15b]. In particular, a neural network nonlinear autoregressive exogenous (NARX) model is used. The configuration is the same as in Case #8 in [GG15a] (p. 414). The ANN comprises an input layer, a single hidden layer consisting of 10 neurons and an output layer. The external inputs are the average consumption profile, as well as weekday and weekend dummy variables. The outputs of the ANN are fed back as inputs using a certain delay. It uses the Levenberg–Marquardt training algorithm, and the data are divided into training (15%), validation (15%) and test (70%) datasets. The training algorithm uses mean square error as the performance function to terminate the training. The overall performance of the model is summarised in Table 5.1.

Table 5.1 Forecasting measures.

Measure	**Wind Generation Forecast (per 1.5 kW)**	**Hot Water Consumption Forecast (kg)**
Mean	0.557 kW	6.145 kg
Standard deviation	0.374 kW	9.269 kg
Mean error	– 0.012 kW	0.042 kg
Standard deviation of error	0.137 kW	1.541 kg
Mean absolute error	0.099 kW	0.870 kg
Root mean square error	0.137 kW	1.548 kg
Normalised mean absolute error [GG15b]	0.264	0.108
Normalised root mean square error [GG15b]	0.368	0.192
Regression value R	0.938	0.981

The controller also implements temperature control. Despite any other factor, the controller attempts to maintain instantaneous temperature within the limits described in Equation (5.3). These are the upper and lower temperature safety bounds. If for any reason the temperature increased above 90 °C, it would disconnect the heating element until the temperature dropped below 88 °C. Similarly, if the temperature dropped below the critical 40 °C, it would turn on the heater regardless of the control signal from the system. This mechanism helps to ensure that the comfort level for the user is not impacted.

5.2.2.3 Wind Imbalance and Normal Consumption

The performance of the system is assessed using previously-measured and -forecasted wind power generation data (total wind generation forecasts, as well as actual wind generation shown in Figure 5.3) provided by the Lithuanian NTSO [GG15c]. The overall goal of the newly-proposed DSM system is to create a backup power aggregator to cover forecasting error. The mismatch between forecast and actual generation can be either positive (surplus of energy) or negative (shortage of energy), and it is being referred to as the imbalance throughout the paper. Minimising imbalance enables renewable electricity sellers to supply the exact amount of electricity. The electricity that sells in the market can be delivered with high certainty, eliminating costly fines for under delivery of power or loss of income due to a lower price of unexpected energy generation (disconnection in the worst case). Table 5.1 contains statistical measures of the wind generation forecast data. The wind generation forecasts throughout the paper are based on the next day-ahead predictions to comprise the electricity day-ahead market. Furthermore, Table 5.1 presents hot water consumption forecast statistical information. It contains the arithmetic average of measures from all houses. These figures are calculated for one hour ahead forecasts.

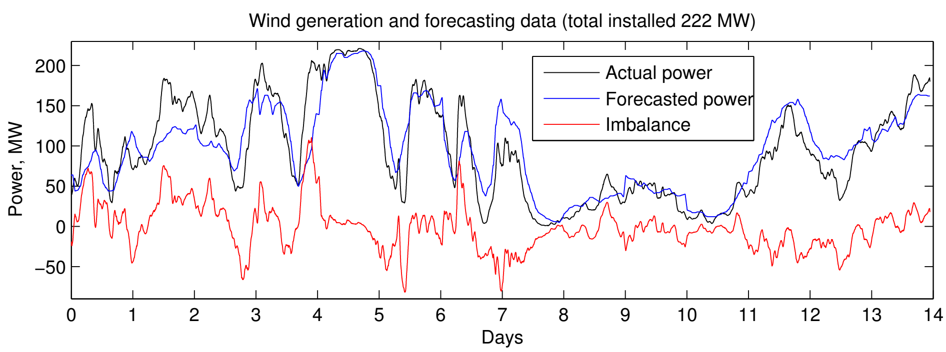

Fig. 5.3 Total actual and forecasted wind power.

Figure 5.4 shows the normal electricity consumption of water heaters (per household) and the normalised wind power imbalance. The wind power imbalance is normalised by assigning 1.5 kW of installed power for every dwelling. The sum of the normal consumption and wind imbalance becomes the target total power consumption for hot water heaters participating in DSM. This way, the residential users can both shed the load (turn off the heating elements inside hot water heaters) or use more energy than they would normally use (turn on the heater, irrespective of the water setpoint temperature). This is particularly useful when compensating the negative imbalance in the system; the users would have to use less energy than they would normally use without DSM (regulation up). It should be noted that individual houses follow different loads specified by the smart controller, but the average target hot water heaters' consumption of electricity is shown in Figure 5.4.

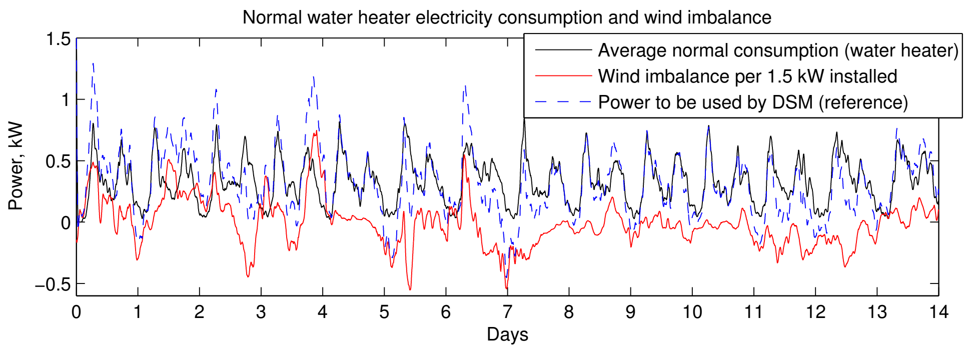

Fig. 5.4 Average normal power consumption, wind power imbalance (fraction of 1.5 kW out of total 222 MW) and power to be used by the proposed demand side management (DSM) system per household.

5.2.2.4 Model Parameters and Assumptions

Modelling such a complex system required the careful selection of parameters, including temperature setpoints, sizes of the tanks, heating element ratings, ambient temperatures, thermal conductivity of the hot water tank, inlet water temperature, *etc*. One of the most important parameters in the context of energy accumulation is hot water tank volume. It describes how long a user can last without using electrical energy (in case of a shortage) or how much excessive electrical energy can be stored (in case of a surplus). In this paper, the hot water tanks were sized between 85 L and 200 L taking into account the average water consumption rate for a particular dwelling. Randomly-picked tank sizes from the chosen range were sorted in ascending order. The highest volume tank was matched to the dwelling with the most hot water consumption, and *vice versa*. Another crucial parameter of water heating devices is the rated power, where it defines how fast the electric energy is transferred to heat. From a demand response point of view, it is important during the times of energy surplus. The heating element power ratings were chosen to fall in a range from 1.5 kW to 2.5 kW [NA99]. The relationship of tank volume and heating elements can be seen in Figure 5.5.

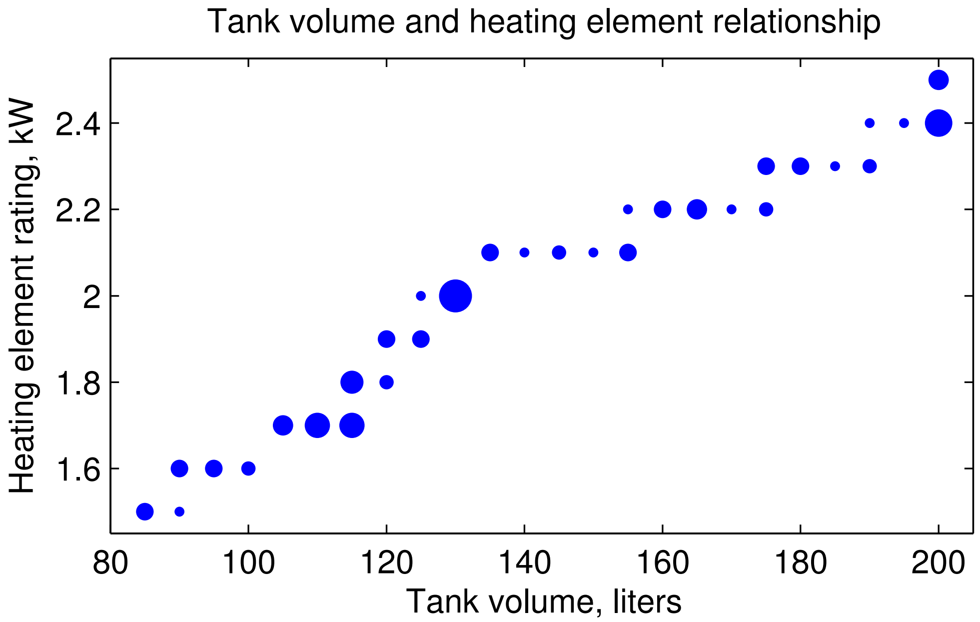

Fig. 5.5 Water heater tank size and heating element power rating relationship.

The inlet water temperature was chosen to be slightly different for all households (between 9 °C and 11 °C) and was kept constant throughout the testing period. Similarly, the ambient air temperature surrounding the hot water tanks was chosen to be between 19 °C and 23 °C. The optimal setpoint temperature was set to be around 68 °C [FFM12].

5.2.2.5 Proposed Demand Side Management System Overall Operation

The main goal of the proposed system is to compensate day-ahead wind generation forecast errors. It enables the supply of the exact amount of wind energy that was sold in the day-ahead market and avoids charges for costly regulation ancillary services. At first, the forecast error is calculated by subtracting the day-ahead forecast from the actual wind generation. This is the power to be regulated using DR. Since water heaters can only consume electricity (regulate down), the imbalance is added on top of the predicted normal consumption to enable up regulation. The predicted normal water heater consumption information can be taken from the distribution system operator or, in this paper, it is modelled by the same ANN. Secondly, the actual electricity usage is aggregated and subtracted from the reference load. It is then used by the demand response controller to compute the request signal for the water heaters, which in turn decides whether to participate in the DR or not. Every 5 min, the controller forecasts individual demand for the next 12 h and computes the ability to participate in the demand response. It is only necessary to forecast 12 h ahead, because it takes about the same amount of time to raise the temperature by 50 degrees for a 200 L tank using a 1.5 kW heating element. Then, the controller computes the worst case scenario and checks whether the temperature is maintained in between the boundaries of comfort. The worst case scenario is achieved by turning the heater off for 5 min and when leaving it to work according to the thermostat. In the case of participation, the water heater reacts to the request signal and alters the energy use accordingly. As a result, the wind forecast error ends up balanced.

The simulation framework comprises 95 dwellings equipped with resistive hot water heater models of different sizes and power ratings, as well as 95 ANN models for every dwelling. The overall system diagram can be seen in Figure 5.6.

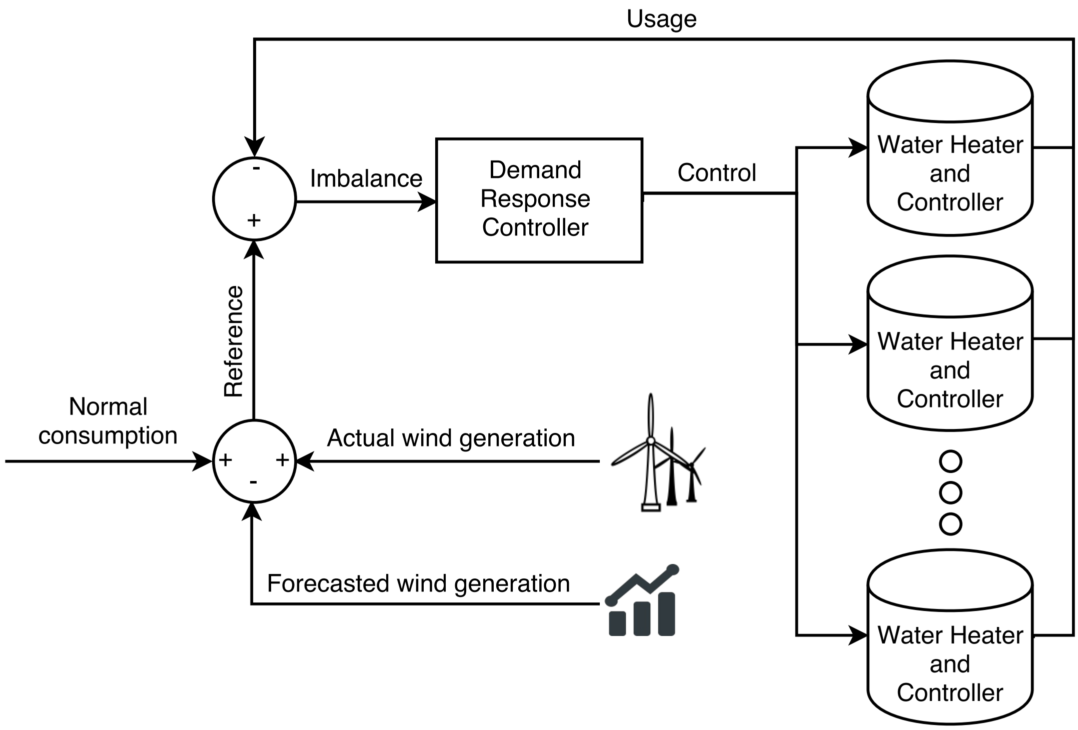

Fig. 5.6 Overall diagram of the system.

5.2.3 Results and Discussion

The simulations were split into three different cases. Each case adds DSM capabilities step by step. Table 5.2 summarises the performance of five different scenarios. Case #1 represents the normal use of hot water heaters without DSM. Case #2 involves DSM, but excludes forecasting of hot water consumption, *i.e.*, it does not look ahead to how much water is to be potentially needed during the next 12 h. In this case, users' comfort is not taken into account and might be compromised. Power in brackets next to the case number in Table 5.2 shows the amount of installed wind power that is on average assigned to every dwelling. It demonstrates the backup power capability of a single unit using the DSM technique. This case involves three different scenarios, – 1 kW, 1.5 kW and 2 kW. Finally, Case #3 depicts the proposed DSM with forecasting and the method of looking ahead. All values are per household.

Performance measures used in Table 5.2 can be summarised as follows:

- Mean power consumption is calculated by simply taking the arithmetic mean of the consumption profile from all dwellings.
- Mean absolute final imbalance is the arithmetic average of final absolute imbalance values. Figures are scaled to be per household per 1.5 kW of installed wind power.
- Mean losses: arithmetic average of thermal losses per hot water heater.
- Mean temperature: arithmetic average of water temperature inside tanks.
- Shortage: average percentage of time the demanded water temperature was not supplied.
- Participation: the average percentage of time that each water heater was participating in DSM. The only time they are not participating is when there is expected high future consumption of hot water; thus, the temperature was expected to drop below critical, so the controller disconnects the particular water heater from DSM (therefore, increasing/maintaining user comfort).

Figure 5.7 shows the relation between the time of shortage of hot water and the tank volume (Case #3). Most dwellings have not experienced any hot water shortage during the simulated period. Houses that suffered from the lack of hot water at some point in time show no correlation between their the tank size. As a result, it can be concluded that the installed tank size does not dictate how suitable the house is for DSM participation.

The results provide evidence that the proposed DSM technique is capable of (1) lowering the energy requirements for hot water preparation and (2) supplying an ancillary service (power regulation) to the grid with a minor change in user comfort. The average energy required to supply the same amount of hot water is decreased due to increased efficiency. Contrary to the traditional temperature control, when the temperature is kept at a constant level and the amount of prepared hot water is inadequate for the amount that is actually needed, the proposed look ahead mechanism forecasts the required amount of hot water and controls temperature in a more efficient way. The temperature inside the water reservoir is decreased during energy shortages, whereas at the times of surplus energy, the temperature is increased to store energy. In fact, user comfort was affected

Table 5.2 Performance measures.

Case	**Mean Power Consumption (W)**	**Mean Absolute Final Imbalance (W)**	**Mean Losses (W)**	**Mean Temperature (°C)**	**Shortage (% of Time)**	**Participation, %**
#1 (N/A)	325.7	144.3	49.4	67.5	0.11	(N/A)
#2 (1.0 kW)	309.4	26.6	54.4	73.1	1.19	100.0
#2 (1.5 kW)	298.7	47.1	52.6	71.4	1.95	100.0
#2 (2.0 kW)	290.0	72.3	51.2	70.0	2.74	100.0
#3 (1.5 kW)	313.9	52.1	46.9	65.9	0.30	94.0

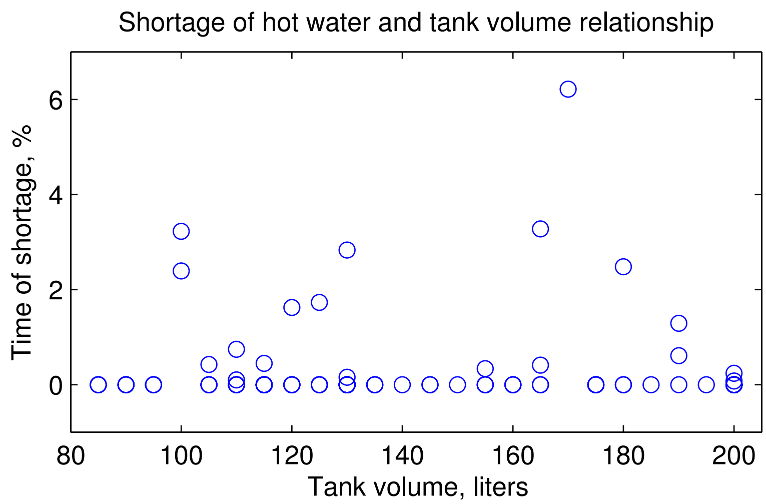

Fig. 5.7 The relationship of water heater tank size and the percentage of time the users experienced a shortage of hot water.

in Case #2, but after demand forecasting was applied, it got restored to nearly the same level (shortage in Table 5.2). Ancillary balancing services become available at virtually no cost, because the users do not notice any major difference in hot water supply due to the correct amounts of hot water that are prepared using forecasting.

5.2.3.1 Limitations

The fact that a negative imbalance can only be compensated by shedding the load leads to a certain limitation. The maximum power that can be shed is equal to the cumulative power the residences would normally use minus the power needed to maintain critically low water temperatures. In this particular case, the hot water consumption profile has very distinctive daily and weekly patterns. The consumption profile does not always coincide with the wind generation imbalance, thus during the valleys of normal energy consumption, there might be insufficient energy to be shed. Clearly, it can be expected that the proposed DSM mechanism will work best during peak hot water consumption periods and, hence, reduce the energy demand from the network. Figure 5.8 demonstrates the average weekly consumption profile.

This hypothesis is confirmed by the scatter plot in Figure 5.9. The scatter plot depicts the relationship between normal power consumption (x axis) and the absolute final power imbalance (y axis). As can be seen, the system is capable of reaching a more accurate final balance during times of higher normal consumption, *i.e.*, when the DSM mechanism has a wider margin for error. Figure 5.10 also confirms this fact. It can be seen that during the times around midnight, the normal energy consumption is low. By subtracting the shortage of energy (caused by negative wind balance), the reference power curve is

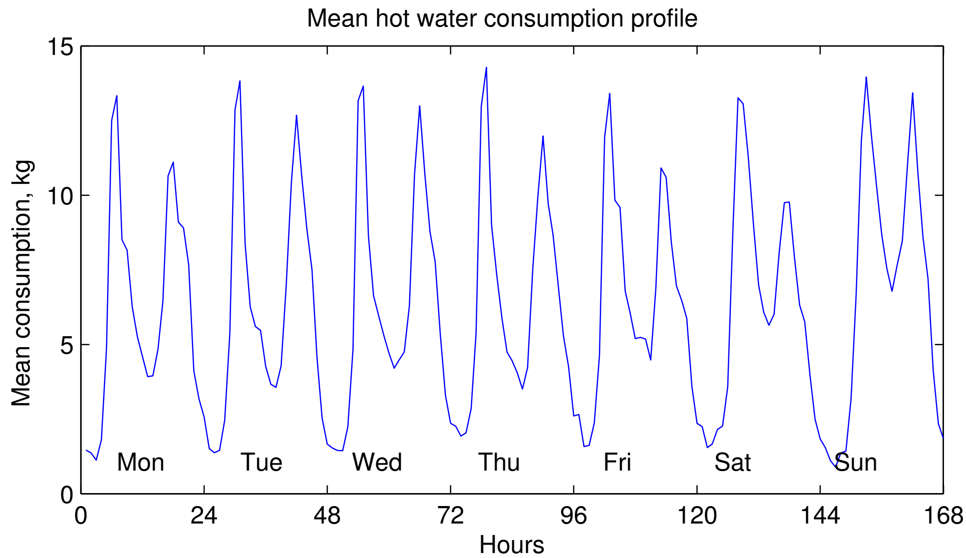

Fig. 5.8 Weekly mean hot water consumption pattern [GG15a].

moved below zero. Obviously, water heaters cannot work in reverse; thus, wind power energy is not fully balanced, and negative dips of final system balance can be seen during these hours.

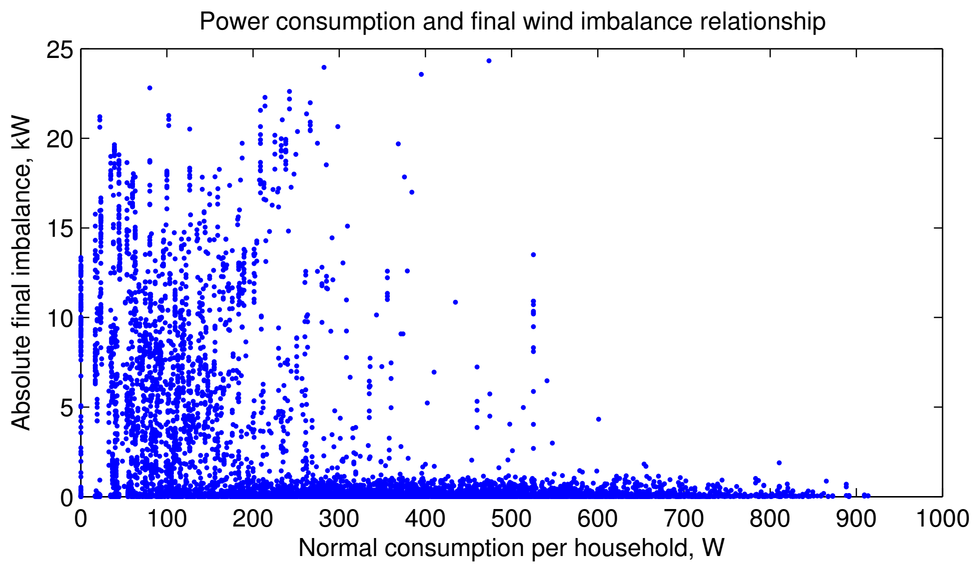

Fig. 5.9 Scatter diagram showing the relationship between normal consumption and final power imbalance.

Another limitation is for the surplus energy, *i.e.*, the maximum positive power imbalance the system can compensate. It is equal to the summed power rating of responsive water heaters (the ones with water temperatures below critically high) minus the forecasted normal consumption. In this paper, the normal consumption forecasts are computed using the same ANN models. As a result, every single dwelling cannot backup more installed

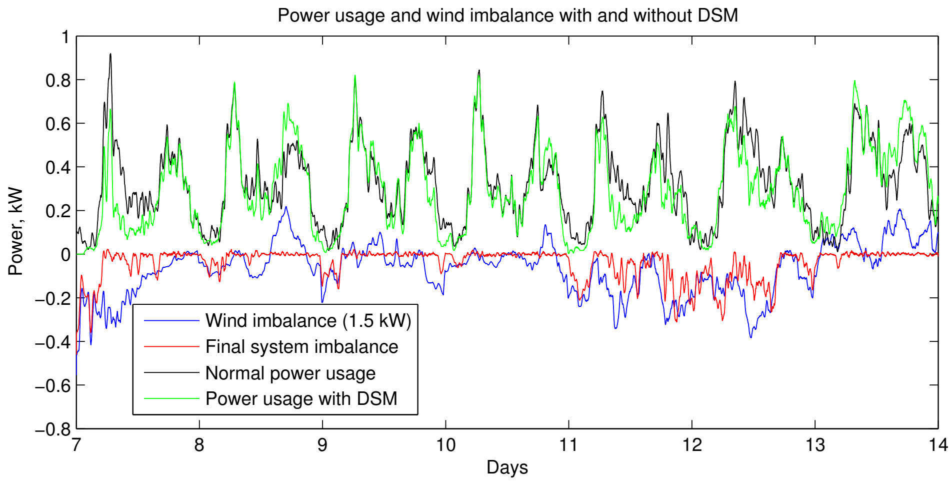

Fig. 5.10 Sample time plot showing alterations in power consumption and wind imbalance. The plot depicts results from Cases #1 and #3.

power than its maximum rating, hence the chosen 1.5 kW value to be backed up by each dwelling. In addition, once the heater is fully charged (critical temperature reached) it is forced to the off state and cannot participate in DR. This creates vulnerability for long periods of surplus energy.

5.2.3.2 Temperatures

Clearly, it is expected that during the normal operation of the hot water heater (no DSM), the temperature does not go above the setpoint. The heater is simply turned off after a certain temperature is reached and turns on when the temperature is dropping. During the high hot water demand periods, the temperature might drop below the given setpoint. Theoretically, the heater should be sized such that it always satisfies users' demands.

In case of hot water heater control using the DSM technique, without look ahead, there might be a situation where the temperature drops below a critical level. Such a situation occurs when an electricity shortage period is followed by substantial demand for hot water. The heating element is simply not capable of transferring heat at the same rate the water is drawn (otherwise, there would be no need for an accumulation tank). This case depicts a situation where the grid is satisfied by sacrificing user comfort (Case #2).

To overcome this problem, a control technique is added, which looks 12 h ahead and takes into account the forecasted consumption at every dwelling. Figure 5.11 depicts the average temperatures of normal consumption (*i.e.*, the setpoint does not change), three DSM scenarios using different amounts of installed wind power to be balanced (per household) and average temperatures using the proposed DSM technique. It can be seen that using the traditional method, the temperature fluctuates around setpoint. In Case #2, three different amounts of backup power force the temperatures to swing in higher amplitudes, respectively. Finally, the mean temperature in Case #3 shows a different pattern, as there is a participation factor introduced to the system, which allows users to choose whether to participate in the DSM or not.

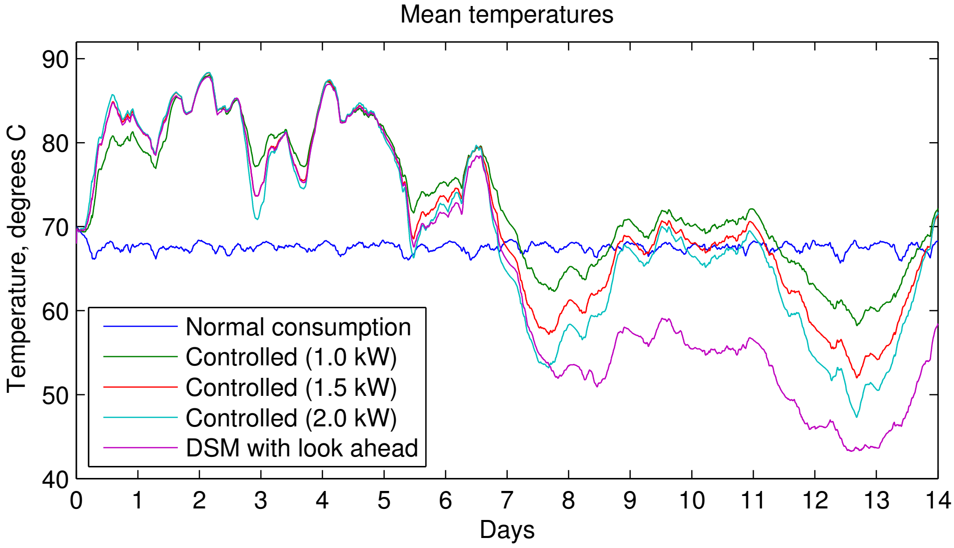

Fig. 5.11 Sample average temperature time plot showing different simulation scenarios.

5.2.3.3 Losses

Thermal losses depend on the thermal conductivity coefficient of the tank walls and the difference in water and air temperatures. Since the thermal conductivity coefficient is constant and room temperature is also fairly constant, losses are mainly a function of temperature. Greater losses are experienced when water temperature is kept high. Therefore, in the event of shifting energy use into the future (delay raising the temperature), the heater exerts less heat waste, and *vice versa*.

5.2.3.4 Energy Balance

Figure 5.10 illustrates the exemplar time plot of energy balancing results from the simulation. It shows the normal consumption and wind power imbalance without DSM. The same figure also depicts the power consumption of Case #3, as well as the final balance that was achieved using DSM with look ahead. Table 5.2 compares the performance measures of the chosen simulation cases. It can be seen that mean power consumption has decreased by about 5% when the DSM technique was applied. The decrease in energy consumption was caused by a higher system efficiency (lower thermal losses), lower final average water temperature and overall negative wind power imbalance. The results suggest that users experienced some hot water shortage in Case #2 due to the fact that 100% of the users were forced to alter their energy use (see sixth and seventh columns in Table 5.2). On the other hand, in Case #3, the look ahead forecasting mechanism allowed the users to decide the most suitable times to participate in order to prevent their comfort violation. It can be seen that using the proposed DSM technique and the current setup, the average of about 94% of users were able to participate. The other 6% were notified by the tailored forecasting models that in case of participation there is a high chance of a hot water shortage. Therefore, user satisfaction was restored and the shortage percentage decreased. At the same time, Cases #2 and #3 demonstrate a decrease in final wind imbalance, *i.e.*, wind generation variation was successfully backed up by the DSM technology. It should also be noticed that mean absolute final imbalance varied in Case #2 due to different amounts of installed wind power per household. The 1.5 kW per household of installed wind power has been observed to be optimal, as higher values cause the system to saturate and increase the final imbalance, which contradicts the key objective of this paper.

5.2.4 Conclusions

Due to the increased number of renewable energy sources, the electricity system requires more ancillary backup services every day. DSM techniques, such as distributed thermal energy storage using individual hot water heaters, can be utilised to tackle this problem. Forecasting hot water consumption at an individual level unveils each users needs; thus, the control can be applied such that the comfort is maintained at almost the same level. By having precise consumption forecasts, it is possible to prepare more accurate amounts of hot water compared to the functioning of a conventional water heater. At the same time, there is a wider margin for DSM operations. Using the proposed technique, time of water shortage increases from 0.11% to 0.3%. Compared to the results of Case #2 (1.95%), the increase in Case #3 is negligible. At the same time, the mean absolute final imbalance decreased by about 64%. The results confirm the initial hypothesis, that using such a DSM technique, it is possible to (1) lower the energy requirements for hot water preparation and (2) supply an ancillary service to the grid with minimal change in user comfort.

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Chapter 6

Hybrid Wind Power Balance Control Strategy using Thermal Power, Hydro Power and Flow Batteries

6.1 Utility Scale Approach for Easier Renewable Energy Integration

As discussed in the previous chapters, the main aim of this thesis is to find novel tools and methods to balance electrical energy. One of the ways to tackle energy balancing problem is discussed in Chapters 4 and 5. These chapters focused on changes made in the residential sector - mainly houses that are equipped with hot water tanks. Alternatively, energy could be balanced using larger industrial energy consumers/generators or utility scale energy storage devices. This chapter analyses exactly that by combining different generator units and flow batteries to work in hand and create ancillary energy balancing service.

6.2 Hybrid Wind Power Balance Control Strategy using Thermal Power, Hydro Power and Flow Batteries

Hybrid Wind Power Balance Control Strategy using Thermal Power, Hydro Power and Flow Batteries

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Abstract

The increased number of renewable power plants pose threat to power system balance. Their intermittent nature makes it very difficult to predict power output, thus either additional reserve power plants or new storage and control technologies are required. Traditional spinning reserve cannot fully compensate sudden changes in renewable energy power generation. Using new storage technologies such as flow batteries, it is feasible to balance the variations in power and voltage within very short period of time. This paper summarises the controlled use of hybrid flow battery, thermal and hydro power plant system, to support wind power plants to reach near perfect balance, i.e. make the total power output as close as possible to the predicted value. It also investigates the possibility of such technology to take part in the balance of the Lithuanian power system. A dynamic model of flow battery is demonstrated where it evaluates the main parameters such as power, energy, reaction time and efficiency. The required battery size is tested based on range of thermal and hydro power plant reaction times. This work suggests that power and energy of a reasonable size flow battery is sufficient to correct the load and wind power imbalance.

6.2.1 Introduction

During the past decade, the number of renewable energy sources has increased dramatically. It is forecasted that the growth of green energy generation will increase even further. Policy makers in developed countries create many incentives in favor of the development of low-carbon technologies and subsidise green energy generation. This should help to reduce carbon footprint and climate change. On the other hand, most of renewable energy comes from generators that are inherently very hard to control [GG14], thus it introduces further complexity in system balancing task.

Up to now in many cases wind turbines or solar panels are being connected to the grid with minimal control. Due to hardly predictable natural resources, like wind or solar irradiation, the errors between actual energy output and forecasted generation are relatively large. This increases the difficulty of the energy balance problem: corresponding operators need either more tools or new technologies to come in hand [LSN12]. Increasing advanced spinning reserve to back up intermittent generation would require inadequate level of investment considering exponential growth of power generation using green technologies. Also, this type of reserve has limited power variation capabilities (in the order of minutes) whereas solar power output can drop nearly instantly. The alternative is to use new highly responsive storage technologies [DGSGBB13, TM13] that could be incorporated into the system and shave over-generation as well as generate energy when demand overtakes supply.

Lithuanian Power System (PS) and other Baltic States currently operate synchronously with IPS/UPS synchronous zone and are connected to BRELL power ring, which consists of Belarus, Russian, Estonian, Latvian, and Lithuanian power systems. According to BRELL regulations Baltic States are not required to have automatic secondary power control, however Baltic States are planning to synchronically connect to the power grid of Continental Europe in 2020. This means decentralisation of power system control and responsibility to maintain power and energy balance within strict boundaries [Uni13]. Therefore, it is important to investigate the feasibility of Lithuanian PS to automatically maintain power balance.

National Renewable Energy Laboratory in USA focuses on researching economic feasibility of energy storage and clearly states that high penetration of variable generation increases the need for all flexibility options including storage [DEKM10]. They also note that the economic value of energy storage devices is at its best when selling to the entire grid, instead of any single source. However the role of storage for wind generation requires continuous analysis and additional studies including new techniques to evaluate more dynamic grid operation.

Droste-Franke et al. analysed German power system balancing options and concluded that technological progress is needed in the following areas [DFPR+11]. Firstly, grid expansion and inter-regional connectivity compensating regional shortages of supply from renewable sources in Europe. Secondly, load management could become feasible through technologies such as smart metering, and finally, storage capacities need to be extended [DFPR+11]. They also conclude that interrupted renewable power smoothing using battery storage system [TM13, HCC+12] is the cheapest option at present.

Söder and Hamon investigate wind power capabilities to participate in balancing services [SH13]. They conclude that wind power plants do not usually participate in balancing services because they must be set to produce less than they are capable in order to be used for up regulation. Margins are kept by spilling the wind, which cannot be stored. A method is proposed to select a certain tertiary reserve control in order to minimise the total cost of the system and maintain stability of the power system with larger portions of wind power. This means that they deal with emergency power system operation modes while our proposed method covers secondary control reserve and optimal share of reserve power between different kinds of generation sources.

Lubosny and Bialek proposed wind farm supervisory control scheme which is suitable to control individual wind mill or separate wind farm in two different ways – using additional storage device or power reserve achieved through part-loading one or more turbines in a wind farm. Authors suggest using wind power filter in order to separate the variability of wind power. They also concluded that elimination of larger power variations can be done more effectively using a central or single energy storage [LB07]. Therefore our proposed control strategy differs due to the fact that it deals with central control of all wind farms instead of individual ones.

Jiang and Wang similarly to [LB07] suggest to control wind power plant using power filter [JW13]. Additionally, they proposed the optimization model of corresponding filter parameters. However, due to the uncertainty inherent in wind power generation, optimal control during long time periods has difficulties predicting wind power and is unpractical in actual real-time operation [JW13]. Besides it requires additional computational resources and time. Active power losses and state of charge of storage devices depend on wind power generation, therefore it is hard to maintain the proper charge level and mitigate wind power fluctuation. Authors conclude that two-time-scale coordination control method gives controversial results because the required battery power reaches 33% of installed wind power (in our case it reaches 5%-25% depending on power system operation mode, discussed later in the paper) while the power fluctuation allowance is up to 10%. Finally, the capacity component of the battery dominates (comparing to power) which means that storage devices are controlled according to wind power trends. The control strategy proposed in this paper controls storage devices according to high frequency component of wind power imbalance and it allows reaching 100% power balance with reasonably lower ratings of storage device.

Abbey et al. suggests using filters and neural networks to control two different types or multiple storage devises [ASJ09]. It is novel and interesting method but too complex for wind power balancing purposes on real-time operation. In principle, multiple levels of storage is needed only in new areas such as island household networks with renewable sources or micro-grids while wind power integration to conventional power systems usually require only short-term storage because the trends of wind power imbalance could be compensated by thermal or hydro power plants in more economical way. Our proposed hybrid wind power balance control strategy composes of conventional generation and energy storage control from power system operator point of view, which means central control in more efficient manner.

Wang et. al studied operational reliability of power system with high wind power penetration [WGB12]. They have concluded that energy storage systems dramatically increase reliability of systems with wind farms. Authors also analyse and show the required battery sizing for certain reliability index.

Khalid and Savkin proposed new semi-distributed storage configuration [KS14b] and using model predictive control [KS10] identified the optimal capacity of battery energy storage system. However the purpose was to identify the optimal capacity only taking into account the system ramp rates while our paper also deals with installed power of energy storage, conventional power plants optimal control and active power reserve optimization. In addition we have used actual wind data of 10 days with a time step of one second instead of 1 day and 10 minutes time step. Yue Yuan et. al. proposed dual-battery energy storage system [YZJ$^+$12] which consist of two separate battery storage systems. One of them is suitable for positive error compensation where the other one is suitable for negative ones. They also proposed three indices for the assessment of the performance on wind power dispatchability which could be identified by using sequential Monte Carlo simulation. However the time step is one hour which means that little dynamic behavior could be represented. The authors also do not introduce any optimization task.

Ansari and Velusami have been investigating the dynamic stability of hybrid autonomous wind – diesel with battery energy storage system [AV10]. They proposed dual mode linguistic hedge fuzzy logic controller and have shown its advantages comparing to traditional fuzzy logic and PI controllers. M. Kalantar and S.M. Mousavi G. replaces less effective and high pollution diesel generator to more flexible and reliable microturbine with the addition of solar array system to earlier investigated one. In order to maximize power outputs of wind and solar power plants they proposed a model reference adaptive Lyapunov controller [KG10] and improve the system behavior comparing to fuzzy logic and PID controllers. Latter Mousavi G. have adapted the proposed method to offshore wind and tidal hybrid system with microturbine and BESS [G.12]. The authors provide an in depth investigation/review of the autonomous rural hybrid system in literature [AV10, KG10, G.12], however the proposed methods are not suitable for wind integration to large power systems with conventional generation, therefore our paper deals with this issue. In addition, our paper represents the optimal wind balancing power allocation between conventional power plants and energy storage devices.

A feasibility study of hybrid solar-wind-battery system for remote location can be found in [MYL14]. Although it shows that it is possible to replace diesel generators by 100% renewable energy, about 48.6% of energy is dumped due to lack of storage and energy management.

Traditional Automatic Generation Control (AGC) system calculates error of the control area and allocates the required regulating power plants. Then they participate in the system balance according to participation factors [ASDG14] in order to keep power system in balance. The participation factors are usually determined according to power plant's parameters such as rate limits [RJ10, GMR12], available spinning reserve [CS12] or economic (cost) characteristics. There are many methods to determine them: major part of power is allocated to the cheapest power plant, the fastest response power plant [BH11] or combined [ASDG14] method. This paper describes energy management method for increasing the quality of wind energy output using conventional Thermal Power Plant (TPP), Hydro Power Plant (HPP) and Flow Batteries (FB).

More proposed ideas of balancing wind power intermittency using energy storage systems can be found in other publications [DMO+10, YNK06, CPL04]. In [DGSGBB13] authors show through simulation how flywheel ESS can be used for wind power smoothening.

6.2.2 The Main Features of Hydro and Thermal Power Plants

In general the limits of power changing rate of TPP and HPP are quite different. The maximum load rate of TPP is about 2% of the installed unit capacity (per minute) while for HPP the maximum load rate could reach 100% of unit size (per minute). However it is impossible to perfectly match the area control error continuously in relation to variations in plants characteristics such as the system frequency, load or wind power plant output. The energy storage devices, such as flow batteries, could significantly improve the flexibility of the system control and reduce the power systems imbalances.

A classical hydraulic turbine could be expressed as:

$$W_H(s) = \frac{\Delta \overline{P_m}}{\Delta G} = \frac{1 - T_w s}{1 + 0.5 T_w s} \tag{6.1}$$

where, $\Delta\overline{P_m}$ is the change in turbine mechanical power, ΔG is the change in gate position, and T_w is the water time constant.

The complete response of hydraulic turbine in respect to gate step change can be seen in Fig. 6.1. Equation 6.1 shows how the turbine output power reacts to a change in position of gate. Figure 6.1 clearly shows that the initial power output of hydraulic turbine is two times opposite the value when the gate is opened immediately. This is due to water inertia which is represented by T_w.

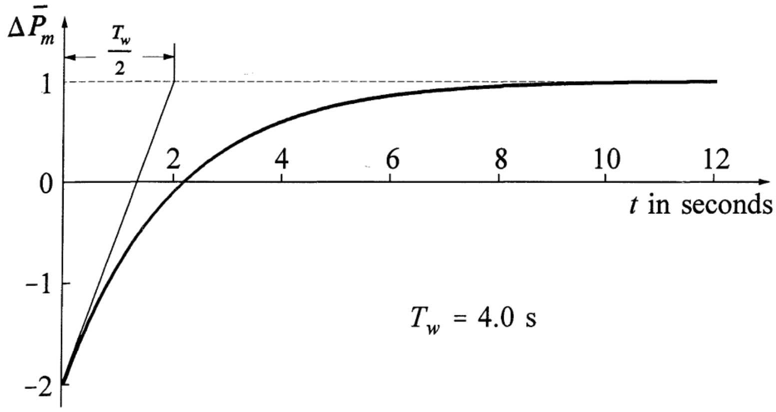

Fig. 6.1 Hydraulic turbine mechanical power output response to gate position step change [KBL94].

Figure 6.2 is included in order to demonstrate the behaviour of main variables of HPP, when the gate position change is a ramp function during one second. It represents relationship between the main HPP parameters - head, power output and water velocity.

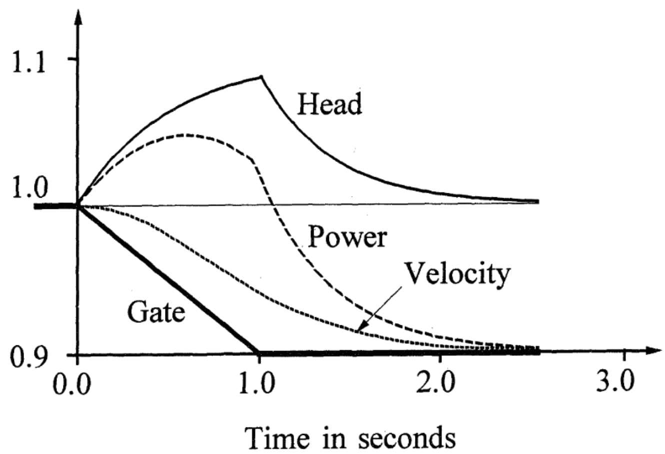

Fig. 6.2 HPP main parameters respect to reduction in gate opening [KBL94].

In order to get stable operation of HPP it is necessary to have permanent and temporary droop compensation when implementing the governors of the hydraulic turbine.

The result is a governor with a high droop for fast speed deviations and a low droop for steady state [Ten10].

The simplified transfer function of the steam turbine with only high pressure section and disclaimer of crossover piping in comparison to reheater could be expressed:

$$W_{Ts}(s) = \frac{\Delta T_m}{\Delta V_{CV}} = \frac{1 + T_{RH} F_{HP} s}{(1 + T_{CH} s)(1 + T_{RH} s)} \tag{6.2}$$

It shows how turbine mechanical torque reacts to change of control valve position. T_{RH} and T_{CH} represent inertia time constant of the reheater and inlet steam chest while F_{HP} shows the fraction of high steam pressure section. Also, T_m is turbine mechanical torque and V_{CV} is control valve position.

The turbine control function is similar to hydraulic turbine. However in order to get stable operation of thermal power plant, it is enough to implement governor with a 4% to 5% speed droop. So there is no need of two types of droop compensation compare to hydro power plant. On the other hand thermal power plant output highly depends on primary fuel system and boiler operation and control. Figure 6.3 illustrates the power output change of TPP in respect to control mode.

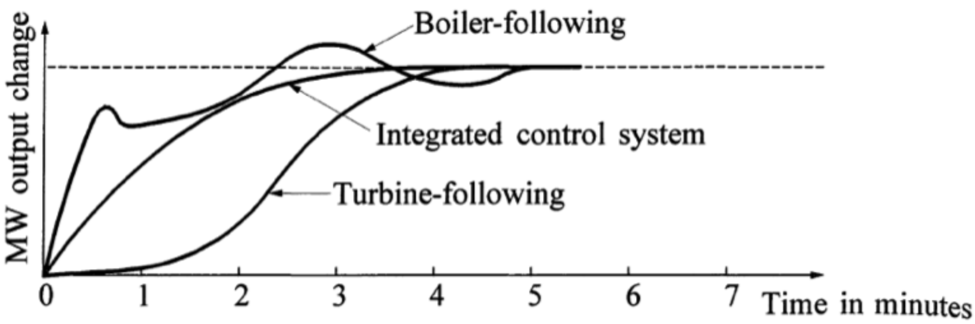

Fig. 6.3 TPP power output in respect to control mode [KBL94].

In the boiler following mode the turbine control valves initiates the changes in generation, while in turbine following mode the changes in generation are implemented by combustion controller [GD].

The typical power outputs of steam and hydraulic turbines are shown in Fig. 6.4. Depending on the boiler type, the control mode and the size of the load change, the power output of thermal power plant might change significantly slower than illustrated. However hydraulic power plant output with a low head could be significantly faster than considered here.

Flow batteries, sometimes called redox batteries (i.e. oxidation and reduction reactions), are electrochemical systems, which are an alternative between the usual batteries and fuel cells [MSA$^+$12]. Flow batteries could be charged as ordinary batteries and

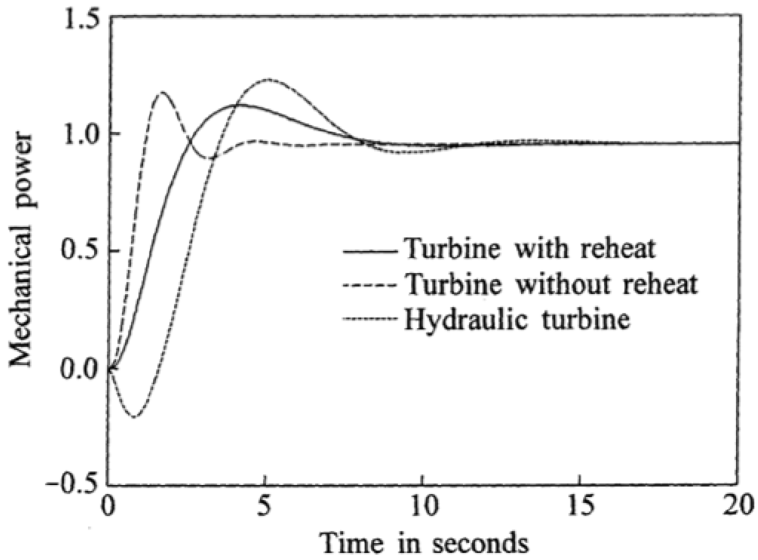

Fig. 6.4 Typical responses of steam and hydraulic units [KBL94].

provide energy as long as charged electrolyte is supplied. The charging and discharging cycles are possible due to reversible electrochemical reaction between two electrolytes [LKW$^+$10]. Conversely charged electrolyte is pumped through separate contours and reaction takes place in special ionic membrane as shown in Fig. 6.5 [Shi11].

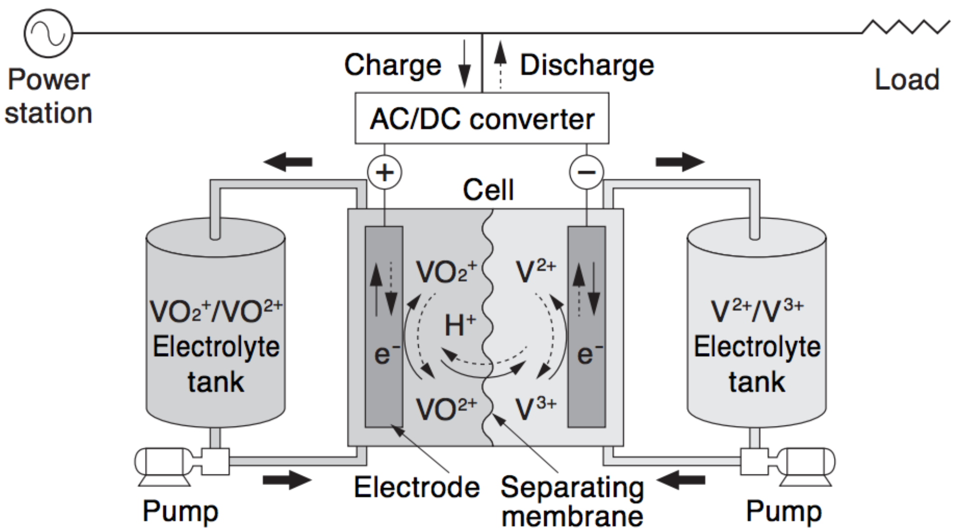

Fig. 6.5 Principle and configuration of a flow battery [Shi11].

The power of flow batteries depends on the surface area of the electrodes. It also depends on the quantity of the bi-pole electrodes. The capacity of flow battery could be increased by expanding the volume of the electrolyte reservoirs, thus increasing the amount of the electrolyte [WMM$^+$11], [BWT$^+$08]. The modules of flow batteries are connected into groups in series to ensure the required voltage, but hydraulic circuits are connected in parallel in order to share electrolyte between groups, therefore the same charging level is ensured [TKH+00].

Some advantages of flow batteries are that they can operate in low temperature and pressure conditions. Also, the electrolyte could be discharged completely [YZC09]. The electrochemical processes are very fast so the reaction time of the batteries is rather small (0.04-0.06 s) and mostly depends on the operation of power electronics. Thus, flow batteries with power ratings in megawatt range could be very useful for power system balance. As it will be seen from the results of investigations the necessary power ratings of FB reaches tens of MW.

6.2.3 Dynamic Models of Hybrid Power Systems

MATLAB Simulink software environment was chosen to model and simulate the system. The goal of this research is to investigate the potential of flow battery technology to serve as energy balancing tool. TPP and HPP are used to cover low and mid-frequency imbalances respectively, whereas FB acts on high frequencies thus a trade-off between conventional power plant equipment wear and required battery size can be observed. It is important to determine the required flow battery parameters (power and capacity ratings) in order to maintain balance in the power system. During this research a model of TPP, HPP and FB was proposed with a control strategy.

6.2.3.1 Control strategy of hybrid power system

The proposed energy balancing method aims to reduce the imbalance of a virtually isolated electric power system. It consists of thermal power plant, hydro power plant, flow battery and a PI controller that mainly deals with the compensation of energy losses related to the flow battery charge/discharge cycle (Fig. 6.6). The model is designed to offer a tradeoff between equipment wear and the required size of the battery. As discussed later in the paper, bigger time constant in the low-pass filter (LPF) requires larger battery size and higher power ratings. The initial error is the difference between the actual power and the forecasted power:

$$P_{error} = P_{act} - P_f \tag{6.3}$$

where, P_{error} is the initial error, P_{act} is actual power and P_f is forecasted power.

The error between the actual and forecasted generation is first fed through rate limiting low-pass filter. It cuts off mid and high frequencies and reduces TPP depreciation costs. Next, the error left after TPP, is fed through another low-pass filter with a slightly lower

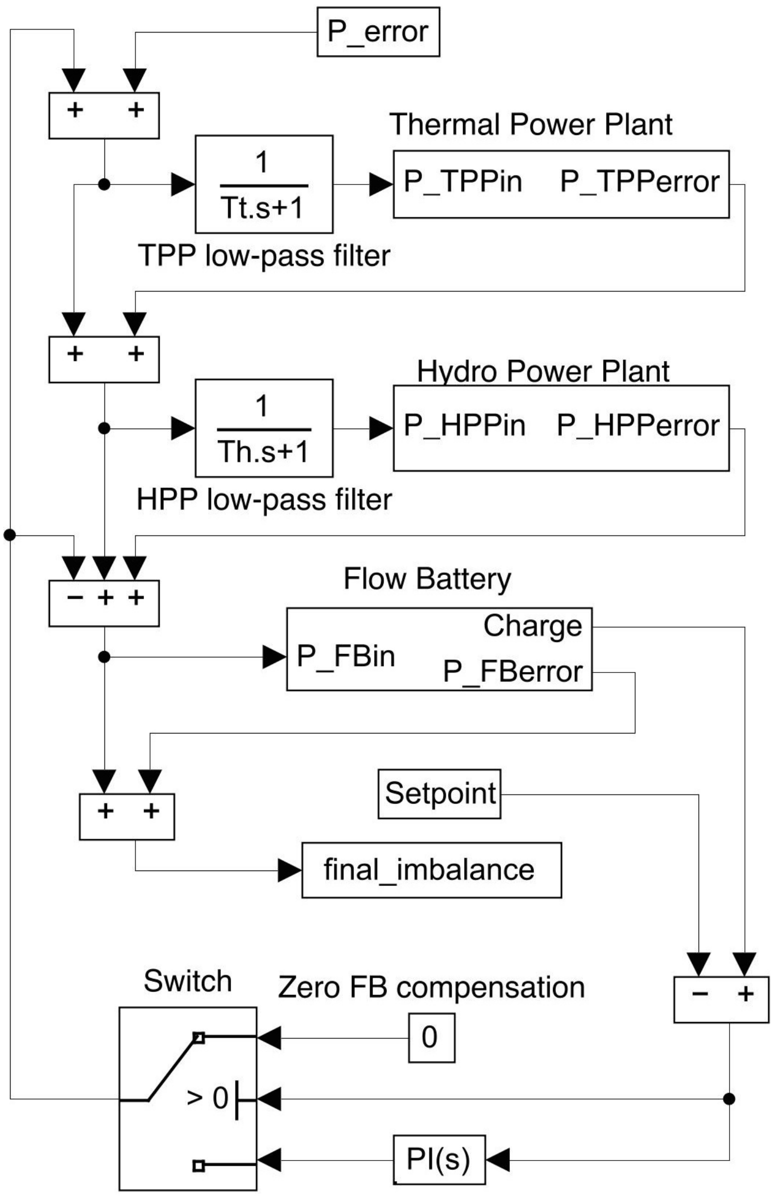

Fig. 6.6 Model of the system.

time constant. This separates the mid-frequency band, which then goes to the HPP as a control input. It is clear that HPP changed its power output according to mid-frequency variations. This technique extends the lifetime of the HPP servo equipment. Generally HPP cannot change its power output very fast due to physical limitations, such as slew rate of the servomechanism and water inertia, which might cause water hammer. Thus, HPP responds by adjusting its power output to compensate only mid-frequency component.

On the other hand, the error that is left (mainly consisting of high frequencies) is then fed to a storage device – a flow battery. The small time constant and high charge/discharge power handles high frequency power fluctuations and smoothens the total power output from the system. Due to the fact that flow battery has a cycle efficiency of about 85% [TBH+09], additional energy to compensate energy losses is required. This is done by the feedback loop that signals TPP and HPP to overcome the losses. The signal adds nearly constant power compensation.

The proposed model is designed so that the average charge in the battery stays around half of its capacity. This deviation in battery charge from half of the capacity is fed to the PI controller as the error i.e. the desired battery charge set point is half the battery size. The controller responds by signalling TPP and HPP to adjust its generation to maintain the charge of FB at the desired level. Again, the charge in FB fluctuates but on average battery charge is kept constant. This level is proposed to be half the total capacity of the battery to be able to equally compensate both energy shortage and surplus. Also, a switch is added to compensate battery losses only when the battery's state of charge is below 50%. The operation of the battery is discussed in greater detail in section 6.2.4.3.

To sum up, the frequency spectrum of the initial imbalance is divided into three bands - low, mid and high. The lowest frequencies are handled by TPP, mid-frequencies are cancelled by HPP and what is left - high frequencies - using a flow battery storage device.

6.2.3.2 Flow Battery Model

The main characteristics of flow batteries were estimated during the process of modeling the flow battery. The model does not take into account any electrochemical processes inside the cell nor the kinetic energy of the electrolyte itself. The main parameters considered were the limits of the power and energy ($P_{min}, P_{max}, E_{min}, E_{max}$), losses (efficiency) and reaction time. The main objective of the flow battery model was to simulate the response to power imbalance. When balancing wind power, the power to be balanced by the FB is determined as the difference between the initial error and power generated by TPP and HPP:

$$P_{FBin} = P_{error} - P_{TPP} - P{-}_{HPP} \tag{6.4}$$

where, P_{FBin} is the power to be balanced by the flow battery, P_{error} is the initial power imbalance, P_{TPP} and P_{HPP} is power generated by thermal and hydro power plants correspondingly.

The main principle is to charge the battery when there is a surplus of energy and to discharge when the energy is scarce. This is depicted in Fig. 6.7. As it can be seen from the model in Fig. 6.8, power of flow battery should be kept within the interval $[P_{min}, P_{max}]$, and energy stored in the flow battery E_{FB} should stay within the limits of $[E_{min}, E_{max}]$. Controlling the flow battery's charge and discharge rate should compensate the high frequency part of the wind power variation from forecasted profile.

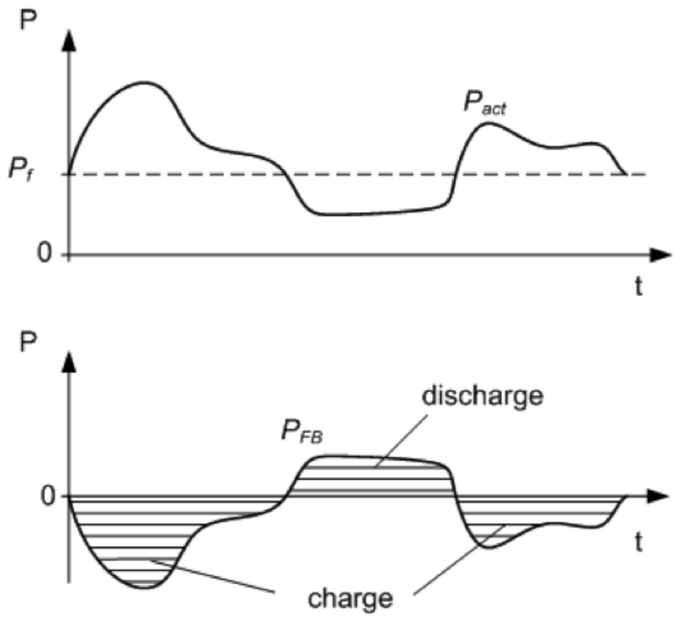

Fig. 6.7 The control principle of the FB. P_{act} - actual wind power, P_f - forecasted wind power, P_{FB} - power of flow battery.

Also, the relative cycle losses are equally divided into charging and discharging losses using the following formula:

$$\eta_{one-way} = \sqrt{\eta_{cycle}}, \tag{6.5}$$

$$L_{one-way} = 1 - \eta_{one-way}, \tag{6.6}$$

$$L_{one-way} = 1 - \sqrt{\eta_{cycle}} \tag{6.7}$$

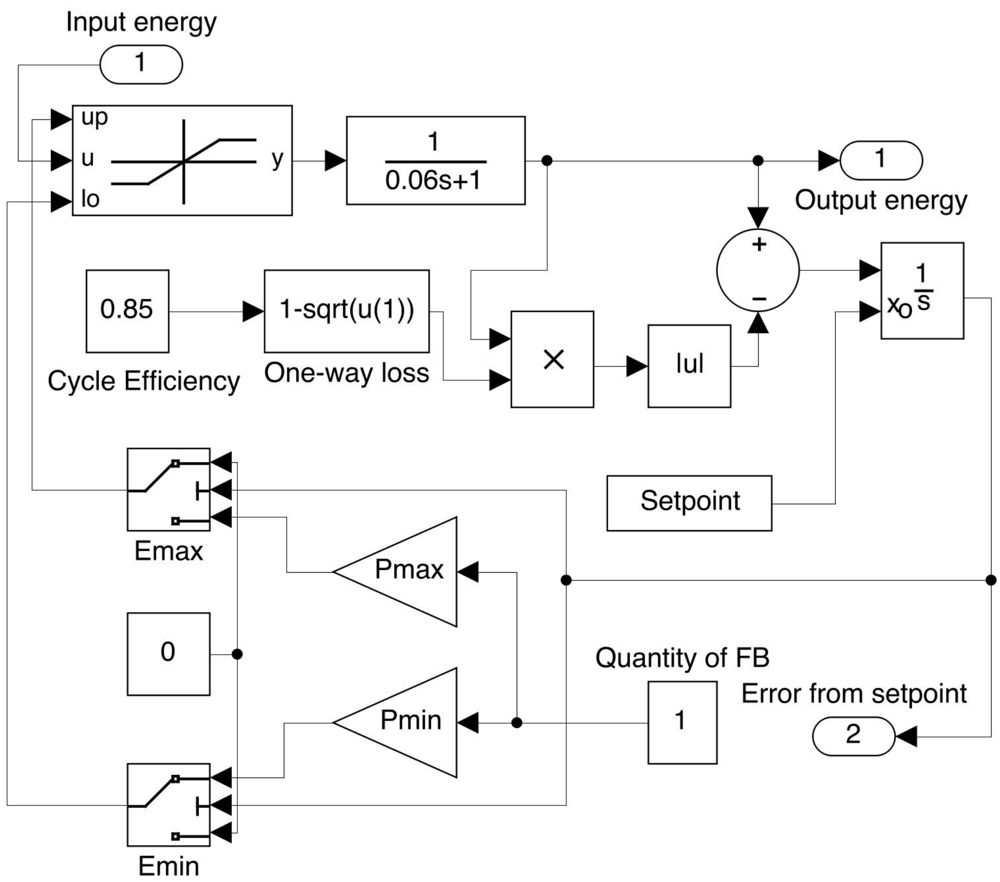

Fig. 6.8 The structure of the flow battery model.

where, $\eta_{one-way}$ is the efficiency of charging or discharging of the battery, η_{cycle} is the total cycle efficiency and $L_{one-way}$ are the losses associated with either charging or discharging of the battery.

Some assumption were made while designing dynamic model of the flow battery:

- The total efficiency of the flow battery cycle is $\eta_{cycle} = 85\%$ [TBH+09],
- The inertia time constant is 0.06 s (considering inertia of power electronics) [Con07],
- The total discharge of the flow battery is allowed ($E_{min} = 0$) [YZC09].

6.2.3.3 Model of Hydro Power Plant

A hydro turbine was used to compensate the imbalance in the system that is left after TPP. The turbine output power follows the load variation trend and aims to reduce the error. It also helps to compensate losses associated with the FB (see Section 6.2.3.1). The HPP was modelled in matlab using traditional governor controller/regulator popularly found in the literature and transfer functions [KBL94]. In particular, a transfer function of hydro turbine is shown in Eq. 6.1 and the block diagram can be found in [Ten10, p. 33]. The rest of the hydraulic turbine and speed regulator model parameters are given in Table 6.1. These parameters are chosen to match Kruonis hydro pumped storage power plant in Lithuania.

Table 6.1 Parameters of the Hydro Turbine.

Parameter	**Notation**	**Value**
Permanent droop	R	0.06
Temporary droop	r	0.5
Temporary droop time constant	T_r	5 s
Auxilary servo motor time constant	T_f	0.2 s
Gate servo motor time constant	T_g	0.2 s
Water time constant	T_w	4 s

The power to be balanced by the HPP is calculated using the following equation:

$$P_{HPPin} = P_{TPPerror} \times \frac{1}{T_{hLPF}s + 1} \tag{6.8}$$

where, P_{HPPin} is the power to be balanced by the HPP, $P_{TPPerror}$ is the power imbalance after TPP and the T_{hLPF} is the time constant of the LPF related to hydro power plant.

6.2.3.4 Model of Thermal Power Plant

Thermal transient process constrains and specific construction of thermal power plant could cause power to vary significantly slower than that of hydro power plant. It only follows the trend and does not reduce the error noticeably. Figure 6.6 represents the whole system and contains TPP block. This block represents a general TPP model and has been created in Matlab according to model found in [KBL94, p. 436].

The model of turbine consists of three cylinders: high pressure, intermediate and low pressure cylinders. Turbine is described with linear model and the transfer function of the turbine is:

$$W_T(s) = \frac{K_H(1+sT_{CO})(1+sT_R)+K_I(1+sT_{CO}+K_L)}{(1+sT_{SC})(1+sT_R)(1+sT_{CO})} \tag{6.9}$$

where, K_H, K_I, K_L - the power of high, intermediate and low pressure cylinders per units; T_{SC}, T_R, T_{CO} - time constants of steam chest, reheater and the crossover between intermediate and low pressure cylinders. Speed governor is modeled as a periodic link of servomotor and power change speed rate limiter which holds the speed within V_{max}, V_{min} values.

The linear mathematical model of the regulating processes of steam turbine speed governor, could be described as second order transfer function W_{SG}:

$$W_{SG} = \frac{1}{(1+sT_{RM})(1+sT_{SM})} \tag{6.10}$$

where, T_{RM} - time constant of speed relay, T_{SM} - time constant of servomotor.

A block diagram of steam turbine can be found in [KBL94, p. 426] and [GD, p. 2]. The parameters of the turbine that was used for the investigation are presented in Table 6.2.

Overall boiler model's transfer function W_B, as boiler's pressure p_B and fuel flow m_{FL} ratio, when considering the constant steam mass flow from boiler:

$$W_B(s) = \frac{e^{-sT_D}}{T_B s(1+sT_{FL})(1+sT_W)} \tag{6.11}$$

where T_D - fuel feed delay time constant, T_{FL} - heat transfer inertia time constant to pipes during fuel burning and T_W - inertia time constant of pipes for heat transfer to water and steam.

Table 6.2 Parameters of the Steam Turbine.

Parameter	**Notation**	**Value**
Steam chest time constant	T_{SC}	0.25 s
Reheater time constant	T_R	5 s
Crossover piping time constant	T_{CO}	0.5 s
Factor of high pressure section	K_H	0.3
Factor of intermediate pressure section	K_I	0.3
Factor of low pressure section	K_L	0.4
Speed relay time constant	T_{SR}	0.1 s
Speed motor time constant	T_{SM}	0.3 s

A block diagram from [GD, p. 2] was used to create Matlab model. Boiler parameters used for the investigation are presented in Table 6.3.

Table 6.3 Boiler parameters.

Parameter	**Notation**	**Value**
Fuel feed delay time constant	T_D	10 s
Boiler heat accumulation time constant	T_B	100 s
Heat transfer to pipes inertia time constant	T_{FL}	7 s
Heat transfer to water and steam time constant	T_{WP}	6 s

The power to be balanced by the TPP is calculated using the following equation:

$$P_{TPPin} = (P_{error} + PI_{out}) \times \frac{1}{T_{tLPF}s + 1} \tag{6.12}$$

where, P_{TPPin} is the power to be balanced by the TPP, P_{error} is the initial power imbalance, PI_{out} is the output from the PI controller and the T_{tLPF} is the time constant of the LPF related to TPP.

6.2.4 Investigation of Wind Power Imbalance

The actual data of wind farms installed in Lithuania was used in this research (Fig. 6.9). In this particular case, it is the forecasted data and the actual wind power data for the period of 1st to 10th of February 2014. The total installed capacity at that date was 222 MW. The mean absolute percentage error (MAPE) of the forecasted wind power during the investigated period was 32% with a standard deviation (SD) of 61 MW. A histogram of the initial errors can be seen in the results section. It should be noted that this period was chosen due to high variation in wind generation as well as high prediction mismatch in order to investigate wind balancing technique in extreme case.

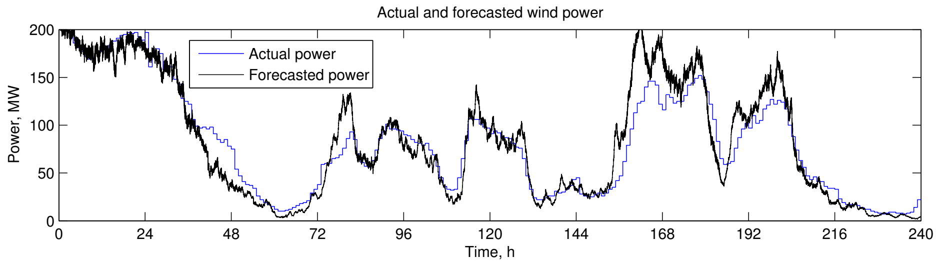

Fig. 6.9 The forecasted and actual wind power for a installed capacity of 222 MW from 1st to 10th of February, 2014.

6.2.4.1 The sensitivity analysis of low-pass filter cut-off frequencies

In order to investigate the influence of the low-pass filters cut-off frequencies to the proposed balancing system, a sensitivity analysis of the low-pass filters time constants have been prepared. Thermal power plant low-pass filter time constant ranging from 0 to 10000 seconds (step of 500 s) and hydro power plant low-pass filter time constant of 0 to 500 seconds (step of 25 s) have been tested. The main parameters of the proposed system, such as the required active power reserve and mean power rates of thermal and hydro power plants, also the required capacity and power ratings of flow battery have then been analysed.

The dependence of required TPP active power reserve, for different low-pass filter cut-off frequencies could be seen in Fig. 6.10, while mean power is shown in Fig. 6.11. The mean power of TPP could represent the total energy generated by the power plant as a regulating energy. It can be clearly seen from the figures that higher cut-off frequencies (lower low-pass filters time constants) increase active power reserve as well as regulating energy of the thermal power plant. It could also be noted that low-pass filter time constant of hydro power plant has minor influence on the thermal power plant specific parameters.

Different situation could be identified in respect to HPP specific parameters. Both the HPP low-pass filter time constant and TPP low-pass filter time constants have appreciable influence. The required active power reserve of HPP is shown in Fig. 6.12, whereas Fig. 6.13 represents mean power of this type of plant.

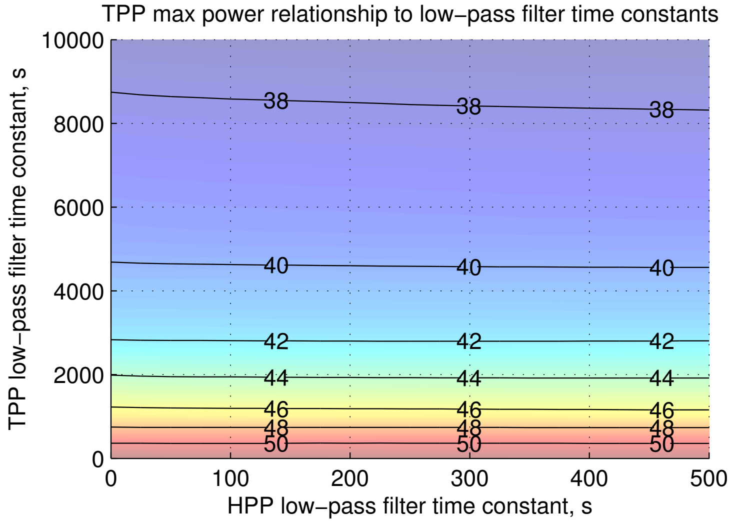

Fig. 6.10 Relationship of required TPP active power reserve with respect to low-pass filter time constants.

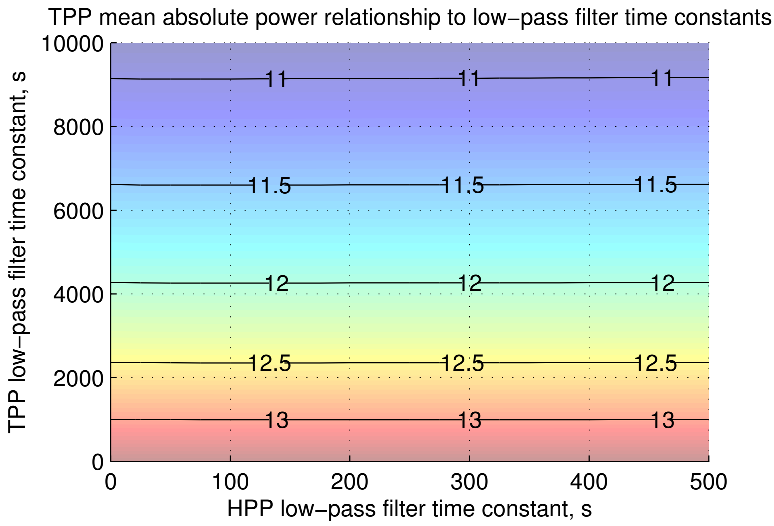

Fig. 6.11 TPP mean absolute power relationship with respect to low-pass filter time constants.

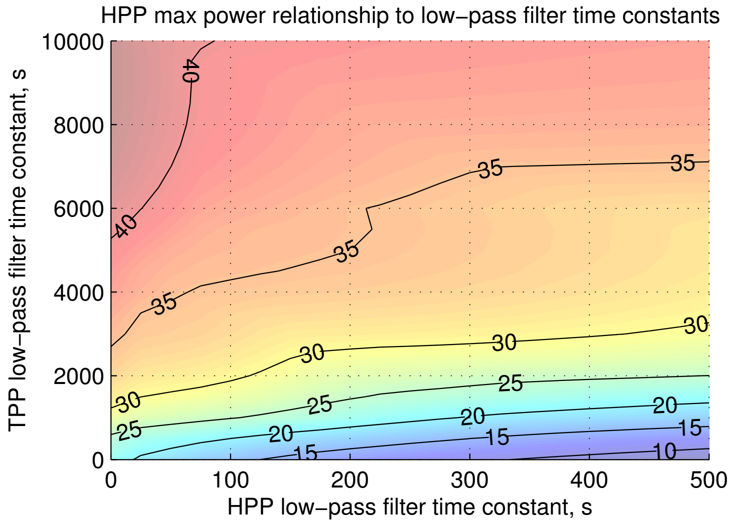

Fig. 6.12 Relationship of required HPP active power reserve with respect to low-pass filter time constants.

Active power reserve of HPP increases when TPP low pas-filter parameter increases and HPP low pass-filter parameter decreases. It could be seen in Fig. 6.12.

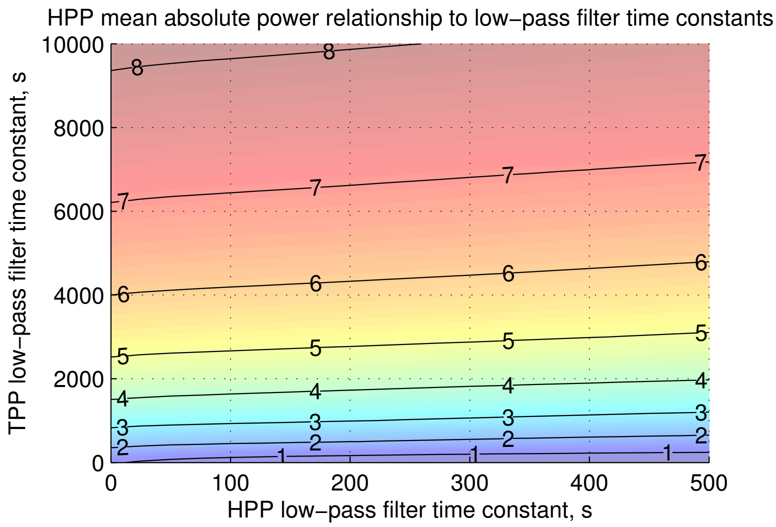

Fig. 6.13 HPP mean absolute power relationship with respect to low-pass filter time constants.

A series of simulations of different low-pass filters time constants have also been run in order to get the flow battery specific parameters, in relationship with different cut-off frequencies. The required flow battery capacity and power range are represented in Fig. 6.14 and Fig. 6.15 respectively. Flow battery required parameters, as shown in the figures, depend on both low-pass filters' time constants. But the main influence is done by the one associated with HPP. As the parameter of HPP low-pass filter time constant increases, the flow battery specifications also increase. It can be noticed that the flow battery mean absolute power relationship to low-pass filters cut-off frequencies is also similar, and taken into account for the analysis.

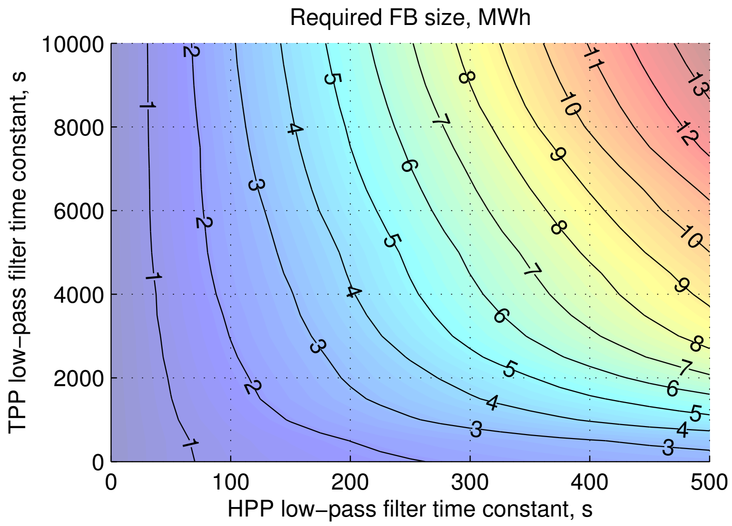

Fig. 6.14 Relationship of required flow battery capacity with respect to low-pass filter time constants.

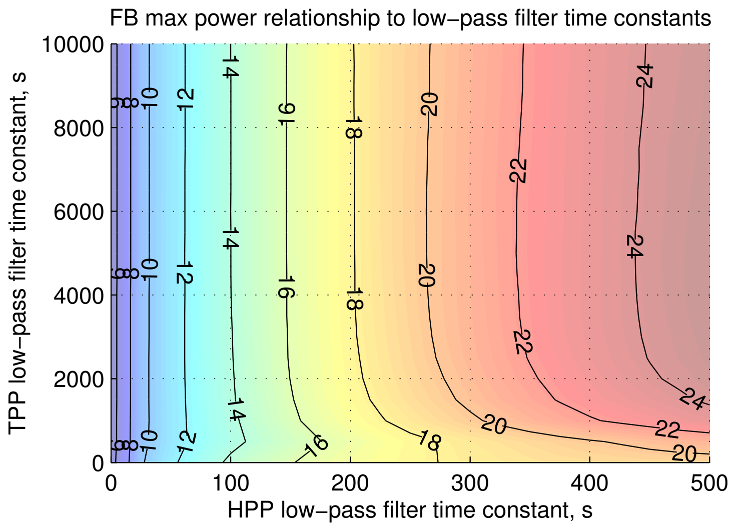

Fig. 6.15 Relationship of required FB active power reserve with respect to low-pass filter time constants.

One of the most important things in this sensitivity analysis is to identify the relationships of thermal and hydro power plants' active power rates, which represent the intensity of power output variation of these power plants as well as the asset depreciation. Thermal power plant mean absolute power rate is represented in Fig. 6.16.

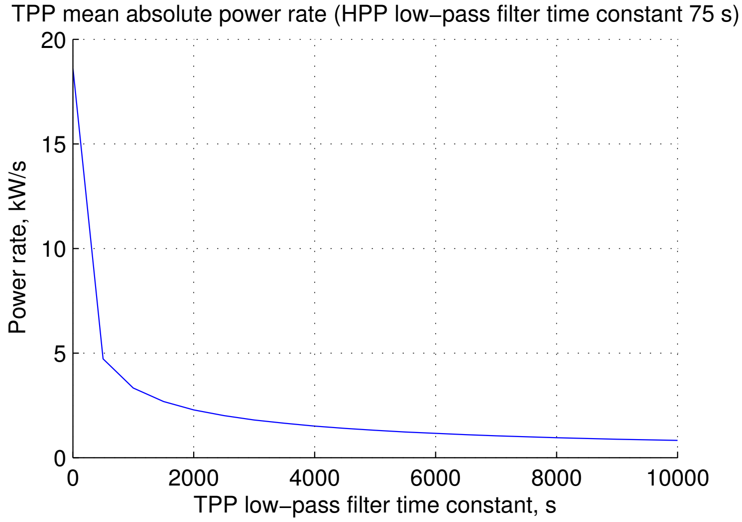

Fig. 6.16 TPP mean absolute power rate with respect to low-pass filter time constant.

The significant mean absolute power rate downfall was identified when thermal low-pass filter time constant increase. In order to show the better visibility the low-pass filer time constant of HPP was kept constant at 75 s. However the full relationship on both filter parameters was assessed in the investigation.

Mean absolute power rate of HPP is shown in Fig. 6.17. Similar results to TPP mean power rate relationship can be observed. A significant drop was identified when hydro power plant's low-pass filter parameter increases. The TPP low-pass filter time constant was also kept constant at 5000 s due to better visualisation of the dependency, while the relationship on both filter parameters was taken into account in this analysis.

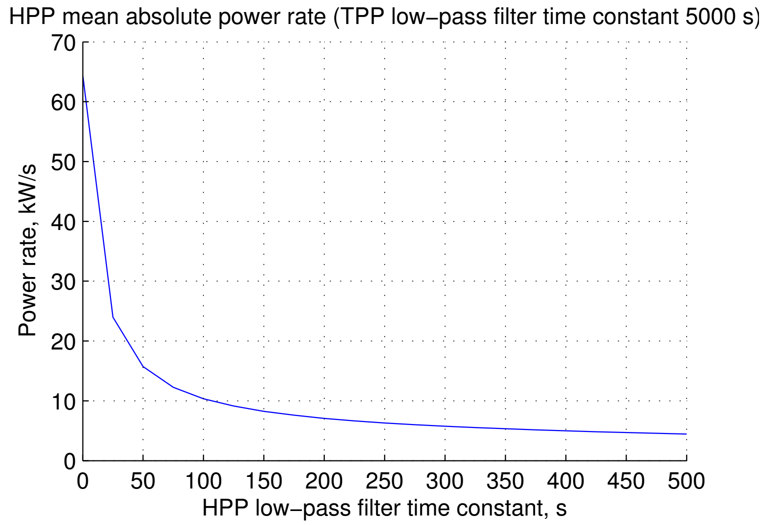

Fig. 6.17 HPP mean absolute power rate with respect to low-pass filter time constant.

6.2.4.2 Optimal low-pass filter parameters identification

Sensitivity analysis presented in the previous section has shown various dependencies of model parameters and relationships. It was identified that required active power reserve in conventional power plant increases as low-pass filter time constant decreases. However specific parameters of the flow battery have opposite relationship as well as active power rates and intensity of traditional power plants regulation. Optimal low-pass filters time constants and cut-off frequencies are investigated in this section.

Objective function was prepared in order to investigate the optimal parameters and the best operation of proposed balancing system:

$$\begin{aligned} min \quad C = C_1 \times P_{TPPmax} + C_2 \times P_{HPPmax} + C_3 \times P_{TPPmean} + C_4 \times P_{HPPmean} + \\ C_5 \times R_{TPP} + C_6 \times R_{HPP} + C_7 \times P_{FBmean} + C_8 \times P_{FBmax} + C_9 \times E_{FB} \end{aligned} \tag{6.13}$$

where P_{TPPmax} and P_{HPPmax} are required active power reserve of conventional power plants, $P_{TPPmean}$ and $P_{HPPmean}$ represents mean absolute power generated by thermal and hydro power plants, R_{TPP} and R_{HPP} are active power rates, P_{FBmean}, P_{FBmax} and E_{FB} are specific parameters of flow battery - active mean power, active power range and required capacity respectively. Finally $c_1, c_2, c_3, ..., c_9$ are relative price corresponding to each of previously mentioned parameters. Different price ratios were used in order to obtain optimal parameters and to avoid conflicts as the price is always controversial. Table 6.4 shows specific relative prices which were used in this investigation. The minimisation of objective function leads to identification of the optimal low-pass filter parameters and overall operation of proposed balancing system.

Results of low-pass filters time constants objective function are represented in Fig. 6.18. The region of the minimum objective function could be seen with the parameters - TPP low-pass filter time constant 5000 s and HPP low-pass filter time constant 75 s. These values will be used in time domain simulations of wind power balancing.

The relationship of the low-pass filter parameters could be expressed:

$$f_c = \frac{1}{2\pi\tau} \tag{6.14}$$

where f_c is the filter cut-off frequency and τ is the filter time constant.

Figure 6.19 shows the initial imbalance of wind power and conventional power plants output generation as well as flow battery output in respect to signal frequency decomposition using identified optimal low-pass filter parameters. It can be clearly seen that low frequencies of initial wind power imbalance are covered by thermal power plant,

Table 6.4 Relative prices.

Parameter	Price notation	Value
TPP reserve power	C_1	0.03
HPP reserve power	C_2	0.02
TPP energy	C_3	0.1
HPP energy	C_4	0.15
TPP mean absolute power rate	C_5	350
HPP mean absolute power rate	C_6	30
FB mean power	C_7	0.005
FB max power	C_8	0.05
FB capacity parameter	C_9	0.1

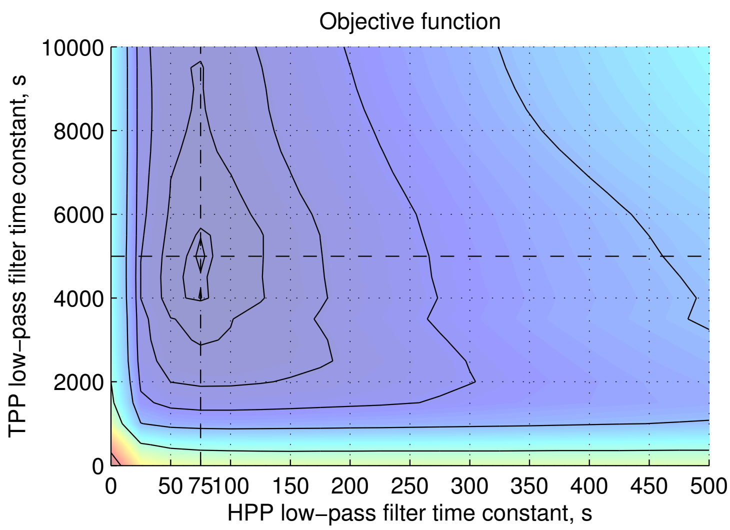

Fig. 6.18 The output of the objective function. A minimum can be seen then time constants are 75 and 5000 for HPP and TPP respectively.

while hydro power plant deals with mid-frequencies and the flow battery eliminates high frequencies.

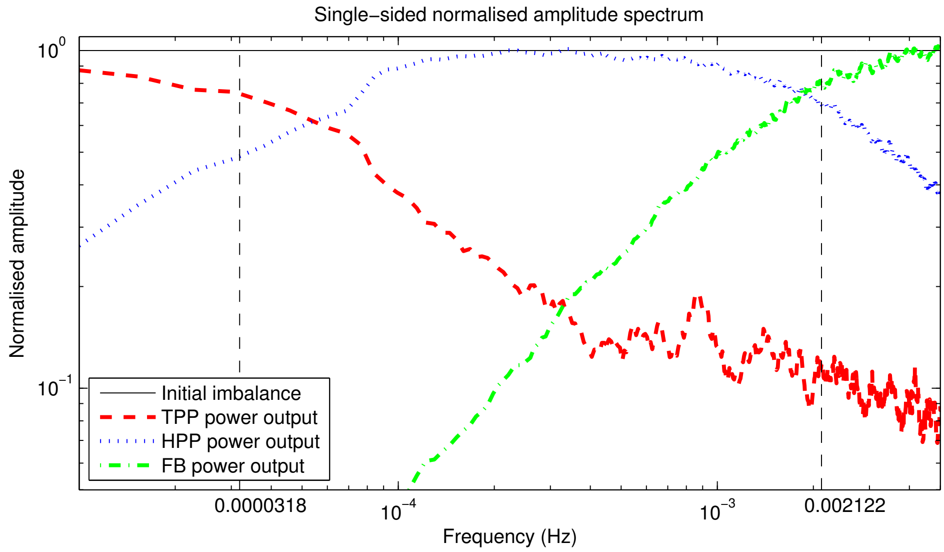

Fig. 6.19 Frequency decomposition of initial wind power and TPP, HPP, FB output powers.

6.2.4.3 The Results of Proposed Balancing Technique

The simulations were run using the chosen optimal time constants of 5000 s and 75 s for TPP and HPP correspondingly and the data from Fig. 6.9. The results are shown in Fig. 6.20. It includes the initial power system imbalance, difference after both TPP and HPP and final imbalance as well as the operating power of TPP, HPP and FB. After the addition of TPP, the initial imbalance SD dropped from 19.5 MW to 9.2 MW. Similarly after the addition of HPP, system imbalance improved to SD of 1.65 MW. Finally, after FB the SD of imbalances were 0.1 MW. Figure 6.21 shows the histogram of initial imbalances in green, imbalances after the TPP in red and imbalances after HPP in blue. From the same graph it can be observed how the spread of imbalances decrease while propagating through the system. It should be noted that addition of TPP and HPP gave positive results and, the mean over-generation of TPP and HPP is equal to mean losses in FB (about 80 kW). This justifies the validity of the model.

The top part of Fig. 6.20 shows a three day simulation period. This period is enough to demonstrate the performance of the system and the nature of TPP and HPP output. The middle part of the diagram also shows a magnified portion of errors (between the time of 12:00 and 13:00 hours of the first day) and, it can be seen how the HPP power tracks the trend of the imbalance after TPP. On the other hand, the bottom part of the graph shows how FB follows the imbalance after HPP and the graph in red is the final

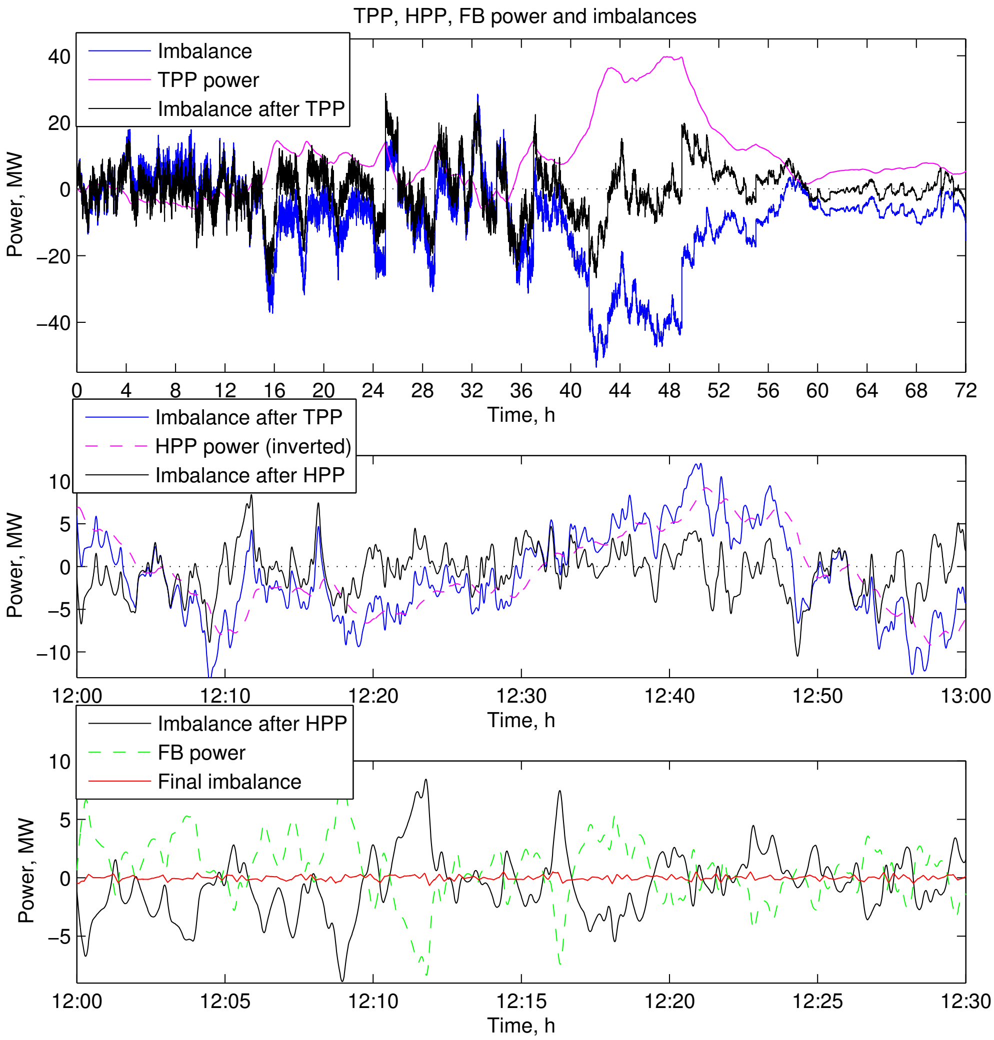

Fig. 6.20 Balancing the difference between actual and forecasted wind power with thermal power plant, hydro power plant and flow battery.

imbalance (time from 12:00 to 12:30 of the first day). The MAPE has now dropped to 0.068%.

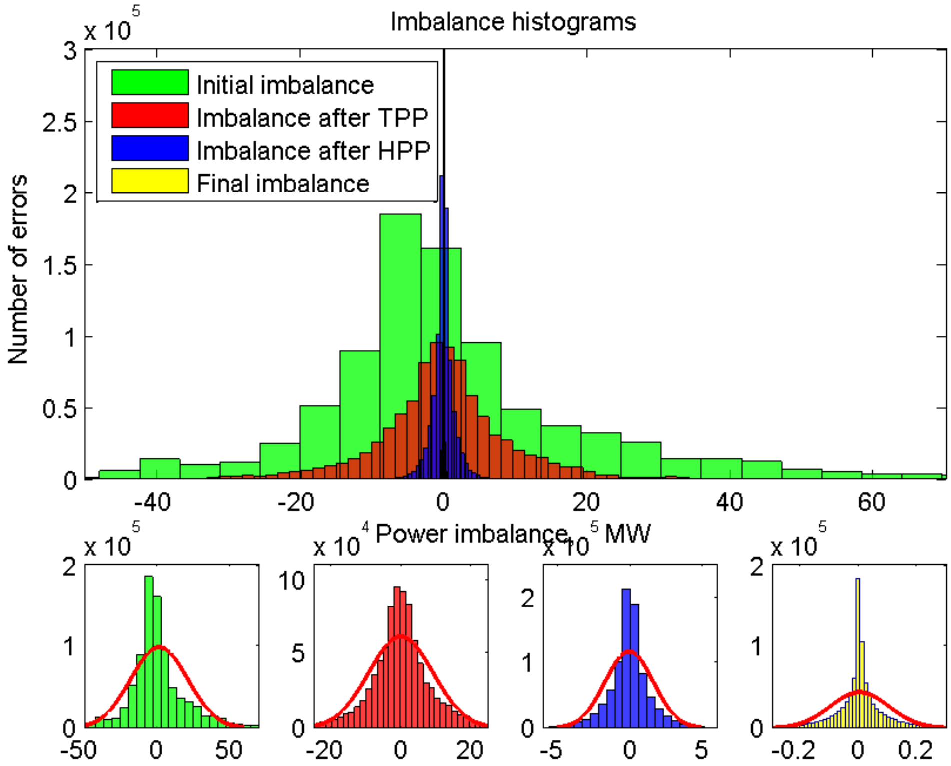

Fig. 6.21 Histograms of imbalances at different stages in the system.

During the investigation, the required power and energy of the flow battery was determined to be 55 MW and 1.90 MWh respectively. This is about 66.4% of the mean wind power during the investigated period and about 24.9% of the total installed wind power capacity in the Lithuanian power system (the total wind power is about 222 MW). A more detailed discussion on why the required FB ratings might be chosen lower can be found in Section 'Limiting the Maximum Required FB Power'. Overall, these results can be considered as feasible for implementation.

Figure 6.22 shows the charge level and accumulative losses in the FB during the simulated period. The required battery size is recorded to be 1.90 MWh. This is the total required capacity in a perfect balance situation. If some power and energy spikes were ignored, the required battery power and size would be considerably lower. To cover the spikes, a super capacitor could potentially be used to serve the required ultra short term power.

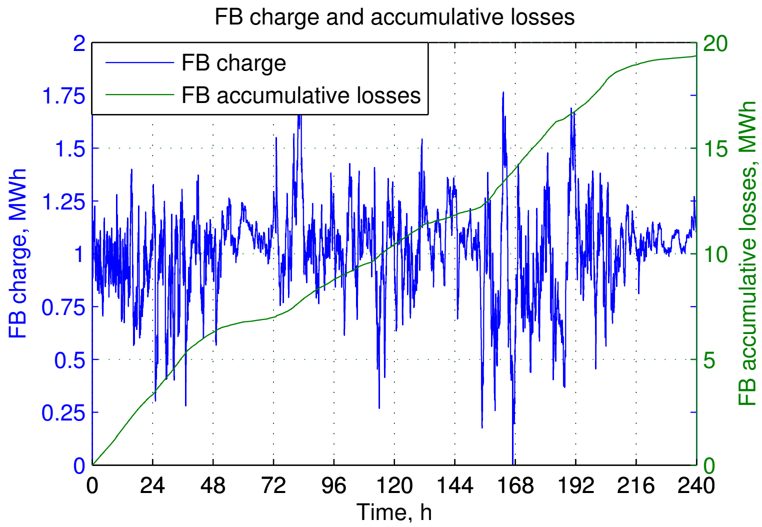

Fig. 6.22 FB charge and accumulative losses.

6.2.4.4 Limiting the Maximum Required FB Power

Considering the SD of power to be balanced by the FB and the three-sigma rule it is reasonable to limit the installed FB power because high power is required during a negligible amount of time. This section discusses the trade-off between FB power rating and the final balance of power.

The data from simulations was extracted to calculate the balanced portion of energy depending on battery power and low-pass filter time constants (Fig. 6.23). The graph shows the FB power and capacity ratings needed to balance different portions of initial energy.

As it can be seen from Fig. 6.23, when 99.7% of energy is balanced, the required FB maximum power is about 14.1 MW. That is a significant drop in the required FB power rating. The required capacity of the FB would also become 1.47 MWh. On the other hand, this limits the power needed for balancing, which results in the increased final imbalance MAPE to 0.073% and a SD to 0.2 MW, but is still quite small compare to initial values (32% and 19.5 MW).

A further decrease in energy capture could be considered. The 95% would correspond to 4.1 MW FB power limit and 0.88 MWh required FB energy and would increase MAPE of final imbalance to 0.14% and SD to 0.58 MW, but is still 43% amount of imbalance improvement compared to the value without hybrid system operation.

6.2.5 Conclusions

The proposed hybrid wind power balancing technique, using TPP, HPP and FB control strategy, presented positive results in balancing the wind power. It also generalises a

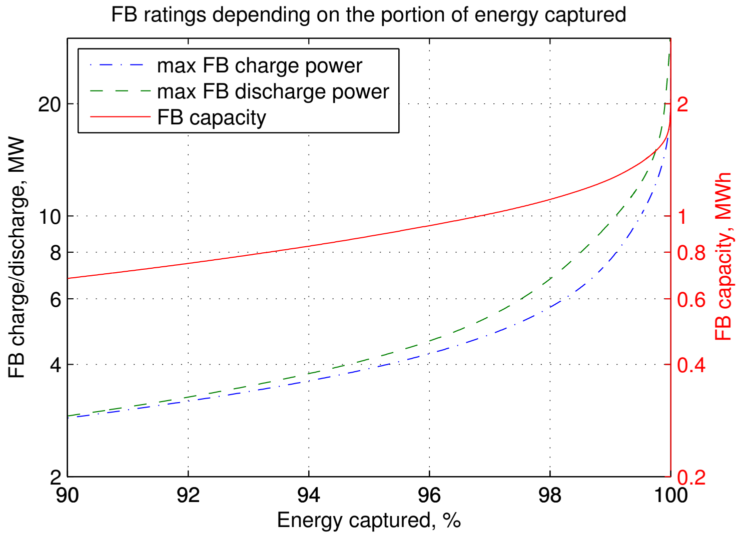

Fig. 6.23 Relative balance dependancy on FB rated discharge and LPF time constant.

Table 6.5 Overview of Results (Imbalances).

Imbalance Stage	MAPE (%)	SD (MW)	ME (kW)
Initial imbalance	32.00	19.52	1291
After TPP	24.36	9.20	-78.9
After HPP	1.44	1.65	-81.5
100% final	0.068	0.10	-0.02
99.7% final	0.073	0.20	1.6
95% final	0.144	0.58	6.3

Table 6.6 Final balance level vs. required FB ratings.

Balance level	FB rated power	FB capacity
100%	55.3 MW	1.90 MWh
99.7%	14.1 MW	1.41 MWh
95%	4.1 MW	0.88 MWh

technique to find the optimal ratings for a flow battery in the Lithuanian power system. However this method could be applied to other electric power systems as well. It might be particularly important to power systems, which operate in island mode.

In this paper, a series of simulations were carried out to identify the cut-off frequencies for the low-pass filters, which optimally controls the power output of thermal and hydro power plants. The optimal cut-off frequency identification enabled the estimation of the required flow battery power and capacity ratings. Also, the paper mainly focuses on the technical side of the method instead of looking at the economical value in detail.

After implementing the proposed control strategy for the TPP, the initial imbalance decreased by about 24% (from 32% MAPE to 24.36%). A further imbalance decrease was reached after the HPP was added - from 24.36% MAPE to 1.44%. After introducing flow batteries, the system became fully balanced. However, it required FB size of 1.9 MWh and power of 55 MW. This constitute to about 25% of the total installed wind power in the Lithuanian power system. Most of the FB's power and capacity is required when the power system is in emergency state. It should be mentioned that such ratings were required when covering every moment in time.

On the other hand, these events are relatively rare, besides some types of flow batteries tolerate overloads for short periods without negative side effects. Making such assumptions the results of additional investigation showed that more reasonable flow battery ratings could be chosen. By covering 99.7% to 95% percent of the power imbalance, it is possible to reduce FB power rating by about 4 to 13 times and FB required capacity from about 23% to 54% (Table 6.5 and 6.6).

Many other storage technologies could be similarly modelled and investigated. In particular, high power and low capacity storage devices, such as super capacitors, could be added to compensate highest frequency imbalances thus highly improving results and reducing power requirements for the FB. Having many different power plants in the model it is then potentially useful to research control strategies in order to reach for the highest economical or environmental benefit.

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Chapter 7

Conclusion and Future Work

This is the final chapter that summarises the outcomes of the research, and reflects on the goals set and success in meeting them. Recommendations for the future work are also provided in this chapter.

Current electricity grid needs expansion and transformation due to increased energy requirements and renewable energy trends. It is also clear that user engagement is the key for reliable and efficient grid operation. This research mainly investigates novel techniques to improve renewable energy integration into today's electricity grid. Chapter 2 recognises the importance of demand side management, investigates demand elasticity and proposes novel user engagement through smart hot water consumption where the device would be connected to the grid.

First and foremost, this research concludes that the use of real-time pricing or other means of signalling can create demand elasticity. The analysis of price and load relationship in Chapter 2 and Chapter 3 demonstrates the ability to shift at least 30 % of total electric energy used by thermal loads (HVAC and domestic hot water) through marginal price changes. It has been demonstrated that fluctuations in consumer behaviour can significantly influence energy balance, thus demand response techniques empower ancillary balancing services. The technique does not violate any economical principles, requires minimal communication bandwidth, and is scalable. Further investigation of user response to shortage of electricity in Chapter 5 demonstrates how an automated system can improve efficiency. It was shown that the use of hot water heater as an energy buffer allowed end user participation in energy balance. Smart thermal resource monitoring and a prediction based system allows sustainable reliability of hot water supply while participating in demand response. The importance of user awareness is clearly emphasised, but it is also clear that these techniques are not possible in manual mode - artificial intelligence is inevitable. In these particular cases the large amounts of data were manipulated to train artificial neural networks.

Another achievement of this research was a successful adaption of artificial neural networks to forecast residential thermal energy usage. Other modelling techniques were also researched. A strongly repeating pattern was discovered in the given hot water consumption time series. Autocorrelation revealed daily patterns as well as weekly patterns. Cross-correlation between different weekdays also showed daily and weekly patterns and also demonstrated that some days are more similar to the others in terms of hot water usage. Individual model average performance was compared to aggregate demand models. All models show positive results and outperform the chosen benchmark models. This work enabled the use of individual consumption forecasts for precise resource control.

An alternative way to balance wind power using hybrid power system was proposed, thoroughly examined and concluded to be successful. The forecast error that comes from renewable wind power plants was considered as the imbalance of an isolated system. As mentioned earlier in the thesis, it would be very useful to be able to generate electricity according to the plan. Unfortunately, wind forecasts almost always introduces inaccuracy. In Chapter 6 it is concluded that this imbalance can be covered using adequate changes in thermal and hydro power plants together with with the help of flow batteries for high frequency variations. Thermal power plants suffer more from load variations than hydro, in both cost and fatigue. A methodology to select different time constants was created to account for this fact. As a result, the simulations show how the wind imbalance is successfully covered using a hybrid power plant system. This research proves that large scale flow batteries can be exploited to sustain reliability and power quality disturbed by large wind energy penetration. Additionally, the work generalises a technique to find the most appropriate flow battery capacity and power rating.

7.1 Key findings and results

The literature review showed that many demand side management techniques already exist. In particular, there are a few scientific papers relating the use of hot water heaters as distributed storage devices, but none were found implementing forecasting of individual dwelling thermal needs at the moment of writing. Recent advancement in communication technologies accelerates research and implementation of smart grid.

Balancing supply with demand is a complex problem. It is not possible to rely on a single technology. Every method has its strengths and weaknesses thus a combination must be used in order to be able to fully respond to the variety of possible disturbances of both generation and consumption sides. As a result, couple of different approaches are required to solve the same wind balancing problem.

The importance of price signalling to the residential user was discovered in the early stage of this research. Simulations using Gridlab-D simulator showed that by fluctuating the price of electricity, with a realistic HVAC setup, it is possible to achieve 21% HVAC load shift and 9% of water heater load shift. This discovery lead to further investigation of residential hot water heaters and their control in order to shift the load. Chapter 3.1 shows that when using artificial neural networks it was possible to accurately compute real time price signal for at least 30 minutes ahead. Successful neural network training of such a complex dataset lead to further investigation and use of ANN.

Many different models were experimented to predict thermal energy use and neural networks proved to give the best results in terms of individual dwelling thermal energy forecasting. As expected, the aggregate forecasting models gave better results compared to individual dwelling water usage forecast in terms of performance. The results showed that on average the forecasting error for individual houses is higher than the aggregate ones. In particular, normalised mean absolute error and R value is about 30% higher, normalised root mean square error doubles and mean absolute scaled error is 15% higher. On the other hand, aggregate forecasting models are not suitable in the proposed demand response technique because it conceals individual demand profiles. This would have considerable user comfort implications, i.e. the controller would try to change the load in similar fashion for all users thus the amount of supplied thermal energy would not be tailored to every single dwelling. Another important result was the discovery of differences in thermal energy demand patterns between working days and weekends. This lead to the introduction of dummy variables showing the day of the week and improving forecasting results.

Another approach to balance wind generation in this research involves utility scale storage. The results of this hybrid power system (222 MW installed wind power) demonstrate that the optimal performance is reached when the response time constants for thermal and hydro power plants are 5000 s and 75 s respectively. In order to fully balance generation deviations caused by wind forecasting error, a flow battery of 1.9 MWh in capacity and 55 MW in maximum power is required. It should be noted that such high ratings are only required in order to cover 100% of wind imbalance. The required FB power ratings decrease about 4 to 13 times and capacity rating by about 23% to 54% in case 99.7% to 95% of power imbalance coverage. So by allowing 0.3% to 5% of imbalance to remain in the system, flow battery ratings are lowered to a very feasible range for such system. The remaining part of the imbalance could be covered by an ultra fast storage device (discussed in Section 7.3).

7.2 Limitations of the study

To start, as most evolvng technologies begin to develop, financial limitations are always a hindering force for growth. Research in energy related sector including real world experiments are financially demanding. A large amount of investment is required in order to implement demand side management experiment and conduct real life tests. As a consequence, computer simulation was the best feasible option for this PhD project.

Secondly, computational capacity limited the timescale of simulations on distributed energy resource management. Following the Moore's law, it is expected that future research will be capable of covering larger timescales thus including wider variety of dynamic water heater responses.

7.3 Recommendation for future research

In the future research, the following improvements to the forecasting models could be made. Additional inputs to the neural network can be added, such as weather information (outside temperature, humidity, solar irradiation, precipitation, wind speed), holiday dummy variables, user programmable schedule (user correction), etc. An interesting water usage pattern has been noticed during Friday and Monday mornings (around 9am). The peaks during these days coincide with the morning peaks from working days. This suggests that long weekends might cause this to happen. As a result, occupants' work schedule might also be taken into consideration when creating these prediction models. Also, since weekday and weekend thermal usage is considerably different it might be suggested to consider two separate models for Monday to Friday and Saturday/Sunday periods. A larger variation (greater irregularities) in weekend data has been noticed thus a better fitting model might exist. Some dwellings showed very high consumption irregularities - perhaps future work might include classification of dwellings depending on how well a particular model forecasts and withdrawal of the poorest performing houses from the demand response program. Looking at the seasonal factors of hot water consumption for every weekday (see figure 4.16) it can be noticed the weekend pattern shift in time. Perhaps a parameter or a dummy variable could be added to the model that represents the amount of time to be shifted when considering autoregressive terms during weekends.

For the future work on hybrid power system, additional ultra fast storage could be added to further decrease the required power ratings of the flow battery. In particular, these could namely be flywheels or super capacitors. It would allow to further decrease the imbalance and share the load with flow-batteries. These devices would correspond to the highest frequency power variations. Furthermore, future work might include different storage technologies (of a similar capacity and power rating) that could substitute flow batteries.

As for the simulation framework, it can be extended to include the communication side of the smart grid and could accurately simulate signal propagation lags introduced by the communication media. Since smart grid requires knowledge from many different disciplines, a collaborative research is highly advised for the development of future smart grid simulation platform. Also, improvements of graphical user interface are necessary.

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Appendix A

Poster publications

A.1 Energy Management Methods in Scalable Smart Grid

Energy Management Methods in Scalable Smart Grids

L. Gelažanskas[a], K.A.A. Gamage[a], C.J. Taylor[a]

FST Christmas conference 2013, Lancaster, UK.

Create, Connect, Grow, ICT 2013 conference, Vilnius, Lithuania.

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Energy Management Methods in Scalable Smart Grid

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Introduction

Supply-demand balancing act in electricity grids is a very demanding task. It requires constant monitoring of the network and very fast response to system changes. Poor regulation might lead to brownouts or even blackouts of the whole country. At the same time, increasing number of renewables add another layer of complexity due to their inherent variability in power output. Luckily, recent advancement in communication and sensing technologies enable the advancement of Smart Grid. It will supply utilities and grid managers with additional set of tools for maintaining system balance and stability.

A novel method is being developed at Lancaster University, which:

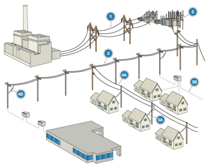
- focuses on Demand Side Management (DSM) technique using real-time pricing (RPT);
- proposes to use state of the art machine learning techniques - Artificial Neural Networks (ANN);
- controls the total consumption using pricing signal;
- assumes that increased number of smart appliances and intelligent Heating Ventilation and Air Conditioning (HVAC) system will contribute in reacting to the state of electricity network.

The main research challenge in this novel technique is to be able to shed the load without creating even bigger peaks of energy consumption at other times.

Electricity grid today vs. Smart Grid

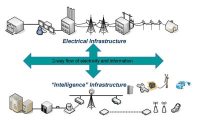
Today's electricity grid

- Electricity grid is outdated.
- Designed for one-way flow.
- Centralised generation.
- Difficult to balance demand with supply.
- Cross-subsidies between users.



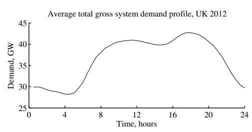
What's new in Smart Grid

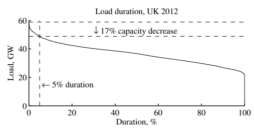
- Current grid needs complete makeover.
- ICT layer on top of electricity grid.
- T&D automation.
- Distributed energy resource integration.
- Smart meters along with EMU's.
- Smart electricity consumption.
- Customer enablement.

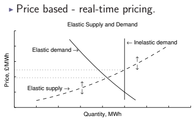


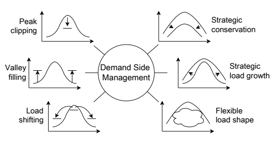
Drivers and benefits of Smart Grid

- Power quality and security
  - Outages and blackouts.
  - Self-healing.
  - Early fault sensing.
- Renewable power integrity
  - Manage renewable energy output.
  - Distributed energy integration.
  - Manage back-up energy assets.
- Enabling technologies
  - Information and Communication technologies.
  - Sensing.
  - Advancement in artificial intelligence.
- Efficiency
  - Increased "virtual" capacity.
  - EV as storage devices.
  - Energy monitoring and control.
  - Decrease carbon emissions.
- Demand response programs
  - Incentive based - direct load control.
  - Price based - real-time pricing.









Problem

- Increasing number of renewables pose threat to system balance.
- Growing demand increases peaks & requires greater capacity.
- Fixed price creates cross-subsidies between users.
- Currently users have no means of knowing about system state.
- Demand and price varies hourly and this is expected to worsen in the future.

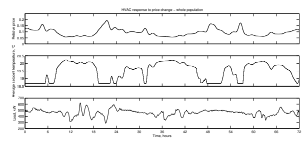
Proposed solution

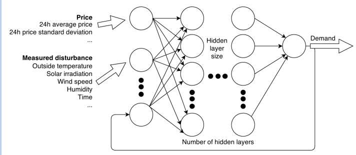
- Implement real-time pricing - this solves cross-subsidies problem and creates control input to the system.
- Model the relationship between real-time price and electricity demand using Artificial Neural Networks. Ultimately it should include measured disturbance variables like weather temperature, humidity, wind speed, etc.
- Implement Neural Network Predictive controller to optimize control inputs (price) for load balance.

Neural Network Model

We assume that it is possible to find a highly non-linear relationship between real-time price and electricity consumption. In particular HVAC system is the main interest. In general, load profile is highly repetitive and human behaviour tends to form habits. These are two key points that help artificial intelligence (AI) learn from past experience and predict future consumption. **Neural networks match there criteria.**

The goal of the Gridlab-D simulation was to capture dynamic relationship between measurable inputs (electricity price and weather information) and electricity consumption of HVAC loads.





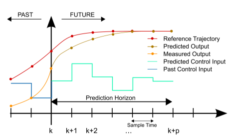
The diagram on the left shows the proposed architecture for NN model. Different parameters to be tested.

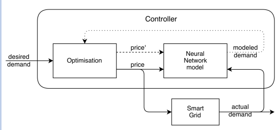
Neural Network Predictive Control

Model predictive control (MPC) is very suitable for this application due to the following HVAC system properties:

- The plant is multi-input, multi-output system.
- Inputs are constrained.
- Disturbances are measurable (e.g. outdoor temperature).
- Time constants large enough for MPC to perform in time.

The graph on the right shows the past and future control inputs and outputs. The reference trajectory in this case is the desired electricity demand. The predicted control input is then calculated while minimising the cost function. In model predictive control strategy, only the first predicted control input is used and the process is repeated for the next step.





The block diagram on the left represents generic neural network predictive controller.

Conclusion

- The proposed technique is a new electricity balancing tool for utilities.
- HVAC load shifting incurs minimal customer discomfort. Load control might even be unnoticed as HVAC system usually has high inertia.
- It is easily scalable - different regions can be isolated.
- Follows standard economic rules - varying price of electricity.
- The technique helps to use assets in the most efficient way.
- Does not require critical mass of participants.
- Does not overload communication path as only price signal is sent periodically.
- Design aims to help integrate renewables that have inherently variable output.

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A.2 Neural Network Based Real-Time Pricing in Demand Side Management for Future Smart Grid

Neural Network Based Real-Time Pricing in Demand Side Management for Future Smart Grid

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IEEE proceedings of PEMD 2014, Manchester, UK.

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Neural Network Based Real-Time Pricing in Demand Side Management for Future Smart Grid

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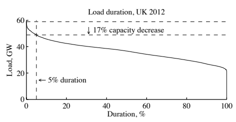
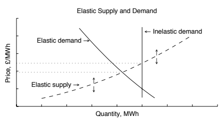
Lancaster University, UK

Introduction

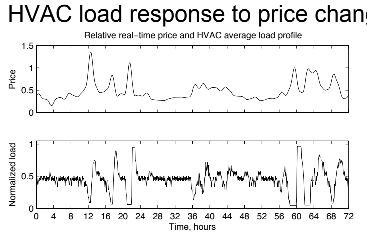
- Increased number of renewables require more ancillary services to backup intermittent power generation.
- Dynamic energy pricing – another demand side management tool.
- Important to understand Price – Load relationship.



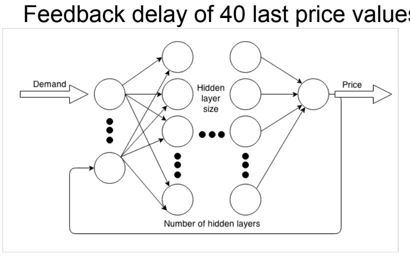


Methods

- GridLab-D was used to simulate data – HVAC load response to price change

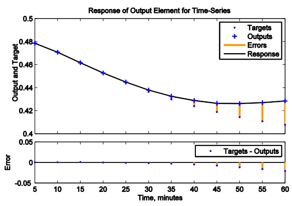


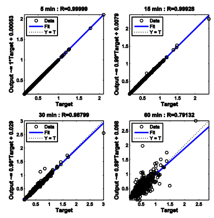
- Artificial Neural Networks were used to learn from past data and predict future price for certain demand.
- Single hidden layer size of 100 neurons
- Input delay of 100 last values
- Feedback delay of 40 last price values



Results

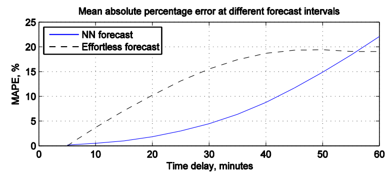
- Performance measure – MSE 2.2x10^{-6}
- Closed loop NN response for 60 min ahead prediction and 5 min, 15 min, 30 min and 60 min correlation



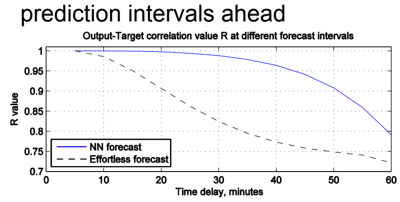


Zero effort prediction f(t) = f(t-1) vs. NN results:

- MAPE for different predictions ahead



- R correlation value for different prediction intervals ahead



Conclusions

NN shows the ability to predict prices required to reach a certain load for at least 30 min ahead.

Appendix B

Conference papers

B.1 Control Strategy for Balancing Wind Power using Hydro Power and Flow Batteries

Control Strategy for Balancing Wind Power using Hydro Power and Flow Batteries

A. Baranauskas[a], L. Gelažanskas[b], M. Ažubalis[a], K.A.A. Gamage[b]

IEEE proceedings of ENERGYCON, (2014) 352-357, Dubrovnik, Croatia.

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Abstract

The increased number of renewable power plants pose threat to system balance. Their intermittent nature makes it very difficult to predict power output thus either additional reserve power plants are required or new storage and control technologies incorporated. Traditional spinning reserve cannot fully compensate sudden changes in renewable energy power plants. A feasible approach to balance the variation in power and voltage (within seconds) is using new storage technologies such as flow batteries. This paper covers the use of flow batteries and hydro power plant to help wind power plants reach near perfect balance i.e. make the total power output as predicted. It investigates the possibility of such technology to take part in the balance of the Lithuanian power system. A dynamic model of flow battery is demonstrated that evaluates the main parameters of it – power, energy, reaction time and efficiency. A range of hydro power plant reaction times are tested in order to find the required battery size. The research and study cases show that power and energy of a reasonable size flow battery is sufficient to correct the load and wind power imbalance.

B.1.1 Introduction

During the past decade, the number of renewable energy sources has increased dramatically. It is forecasted that the growth of green energy generation will increase even further. In fact, developed countries' policy makers create many incentives in favor of the development of low-carbon technologies and subsidize green energy generation. This should help to reduce carbon footprint and climate change. On the other hand most of renewable energy comes from generators that are inherently very hard to control [GG14], thus it adds complexity in system balancing task.

Up to now in many cases wind turbines or solar panels are being connected to the grid with minimal control. Due to hardly predictable natural resources like wind or solar irradiation, the errors between actual energy output and forecasted generation are relatively large. This increases the difficulty of the energy balance problem – corresponding operators need either more tools or new technologies to come in hand. Increasing traditional spinning reserve to back up intermittent generation would require inadequate level of investment. Also this type of reserve has limited power variation capabilities (in the order of minutes) whereas solar power output can drop near instantly. The alternative is to use new highly responsive storage technologies that could be incorporated into the system and shave over-generation as well as generate energy when demand overtakes supply.

Currently Lithuanian power system and other Baltic States operate synchronously with IPS/UPS synchronous zone and are connected to BRELL power ring, which consists of Belarus, Russian, Estonian, Latvian, and Lithuanian power systems (PS). According to BRELL regulations Baltic States are not required to have automatic secondary power control. Although, Baltic States are planning to synchronically connect to the power grid of Continental Europe in 2020. This means decentralization of power system control and responsibility to maintain power and energy balance within strict boundaries [Uni13], therefore it is important to investigate the feasibility of Lithuanian PS to automatically maintain power balance.

Traditional Automatic Generation Control (AGC) system calculates the error of the control area and allocates the associated regulating power plants. Then they participate in the system balance according to participation factors [ASDG14] in order to keep power system in balance. The participation factors are usually determined according to power plant's parameters such as rate limits [RJ10, GMR12], available spinning reserve [CS12] or economic (cost) characteristics. There are many methods to determine it - major part of power is allocated to cheapest power plant, fastest response power plant [BH11] or combined [ASDG14] method.

The rest of the paper covers energy management method for increasing the quality of wind energy output using conventional Hydro Power Plant (HPP) and Flow Batteries (FB).

B.1.2 Overview of the Flow Battery Technology

Flow batteries, sometimes called redox batteries (i.e. oxidation and reduction reactions), are electrochemical system, which are an alternative between the usual batteries and fuel cells [MSA+12]. Flow batteries could be charged as ordinary batteries and provide energy as long as charged electrolyte is supplied. The charging and discharging cycles are possible due to reversible electrochemical reaction between two electrolytes [LKW+10]. Conversely charged electrolyte is pumped through separate contours and reaction takes place in special ionic membrane as shown in Fig. B.1 [Shi11].

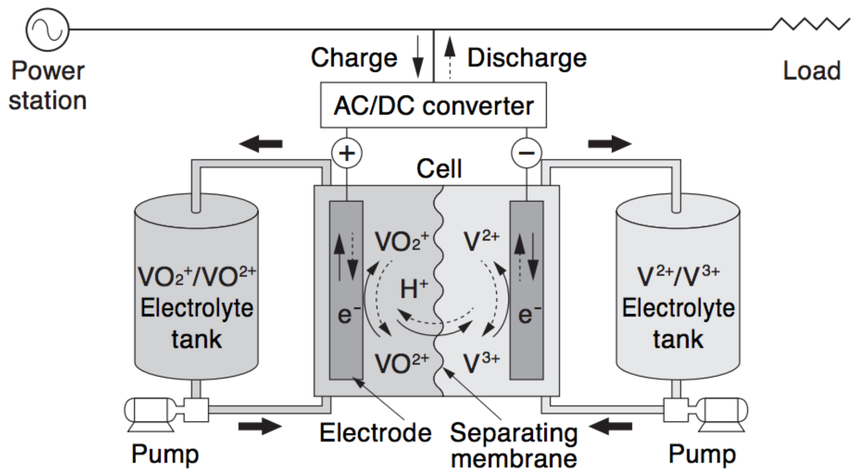

Fig. B.1 Principle and configuration of a flow battery [Shi11]

The power of flow batteries depends on the surface area of the electrodes. It also depends on the quantity of the bi-pole electrodes. The capacity of flow battery could be increased by expanding the volume of the electrolyte reservoirs, thus increasing the amount of the electrolyte [WMM+11]. The modules of flow batteries are connected into groups in series to ensure the required voltage, but hydraulic circuits are connected in parallel in order to share electrolyte between groups, therefore the same charging level is ensured [TKH+00].

Some of the advantages of flow batteries are that they can operate in low temperature and pressure conditions. Also, the electrolyte could be discharged completely [YZC09]. The electrochemical processes are very fast so the reaction time of the batteries is rather small and mostly depend on the operation of power electronics. Thus, flow batteries with power ratings in megawatt range could be very useful for power system balance.

B.1.3 Dynamic Models

MATLAB Simulink software environment was chosen to model and simulate the system. The goal of this research is to investigate the potential of flow battery technology to serve as energy balancing tool. HPP are used to cover low frequency imbalances whereas FB acts on high frequencies thus a tradeoff between HPP equipment wear and required battery size can be observed. It is important to determine the required flow battery parameters (power and capacity ratings) in order to maintain balance in the power system. During this research a model of HPP and FB was proposed as well as the control strategy.

B.1.3.1 Control strategy of HPP and FB system

The proposed energy balancing method aims to reduce the imbalance of a given virtually isolated electric power system. It consists of hydro power plant, flow battery and a PID controller that mainly deals with the compensation of energy losses in the flow battery (Fig. B.2). The model is designed to offer a tradeoff between HPP wear and the required size of the battery. As discussed later in the paper, the bigger the time constant in the low-pass filter (LPF), the larger the battery size and higher the power ratings required. The initial error is the difference between the actual power and the forecasted power:

$$P_{error} = P_{act} - P_f \tag{B.1}$$

where, P_{error} is the initial error, P_{act} is actual power and P_f is forecasted power.

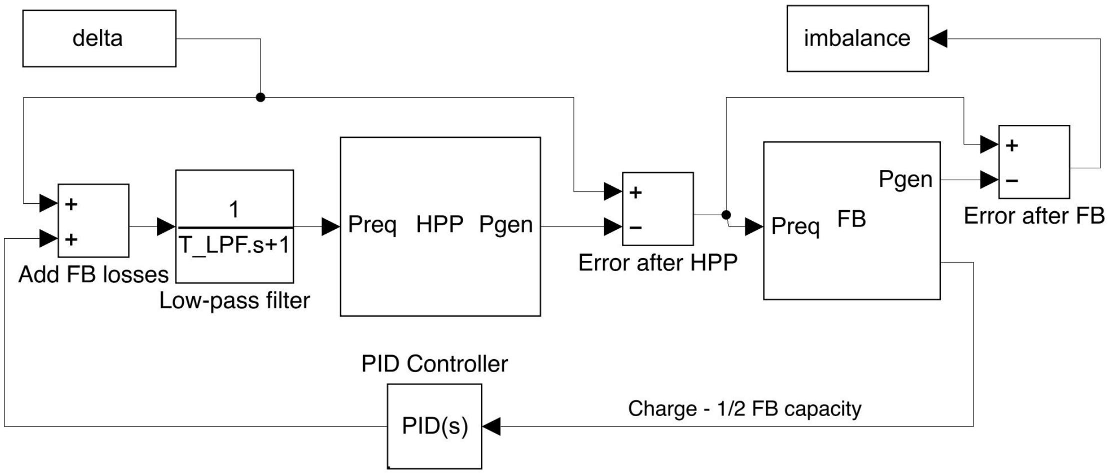

Fig. B.2 Model of the system

The error between the actual and forecasted generation is first fed through rate limiting low-pass filter. It cuts off high frequencies and extends the lifetime of the HPP servo equipment. The other reasons why HPP cannot change its power output very fast are physical limitations, such as slew rate of the servomechanism and water inertia, which might cause water hammer. Thus, HPP responds by adjusting its power output to compensate only low frequency component.

On the other hand, the error that is left (mainly consisting of high frequencies) is then fed to a storage device – a flow battery. The small time constant and high charge/discharge power handles high frequency power fluctuations and smoothens the total power output from the system. Due to the fact that flow battery has a cycle efficiency of about 85 % [TBH+09], additional energy to compensate energy losses is required. This is done by the feedback loop that signals HPP to overcome the losses.

The proposed model is designed so that the average charge in the battery stays around half of its capacity. This deviation in battery charge from half of the capacity is fed to the PID controller as the error i.e. the desired battery charge set point is half the battery size. The controller responds by signaling HPP to adjust its generation to maintain the charge of FB at the desired level. PID controller was chosen for its simplicity and robustness. Again, because only the low frequencies can be passed to the HPP, the charge in FB fluctuates but on average battery charge is kept constant. This level is proposed to be half the total capacity of the battery to be able to equally compensate both energy shortage and surplus. The operation of the battery can be seen in Fig. B.10 [BWT+08].

B.1.3.2 Flow Battery Model

The main characteristics of flow batteries were estimated during the process of modeling the flow battery. The model does not take into account the electrochemical processes inside the cell nor the kinetic energy of the electrolyte itself. These main parameters were considered – the limits of the power and energy ($P_{min}, P_{max}, E_{min}, E_{max}$), losses (efficiency) and reaction time. The main objective of the flow battery model is to simulate the response to power imbalance. When balancing wind power, the power to be balanced by the FB is determined as the difference between the initial error and the power generated by the HPP:

$$P_{FBin} = P_{error} - P_{HPP} \tag{B.2}$$

where, P_{FBin} is the power to be balanced by the flow battery, P_{error} is the initial power imbalance and P_{HPP} is the power generated by hydro power plant.

The main principle is to charge the battery when there is a surplus of energy and to discharge when the energy is scarce. This is depicted in Fig. B.3. As it can be seen from the model in Fig. B.4 the power of flow battery should be kept within the interval $[P_{min}, P_{max}]$, and the energy stored in the flow battery E_{FB} should stay within the limits of

$[E_{min}, E_{max}]$. Controlling the flow battery's charge and discharge rate should compensate the high frequency part of the wind power variation from forecasted profile.

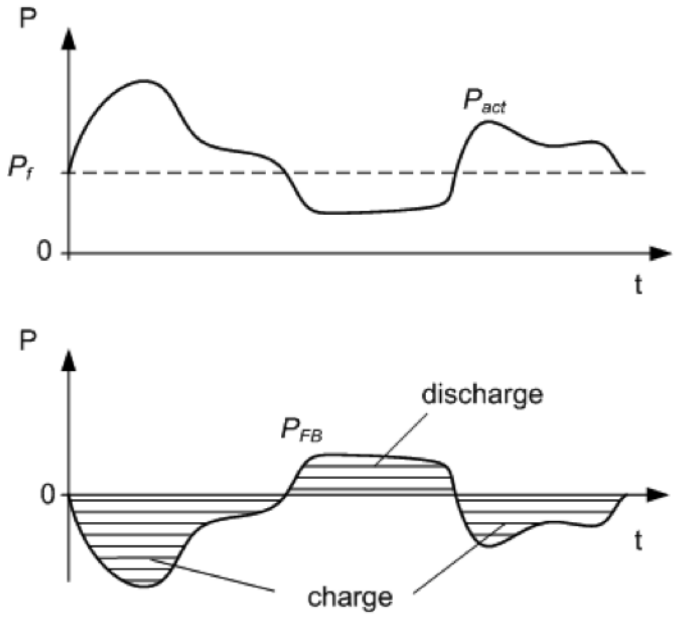

Fig. B.3 The control principle of the FB

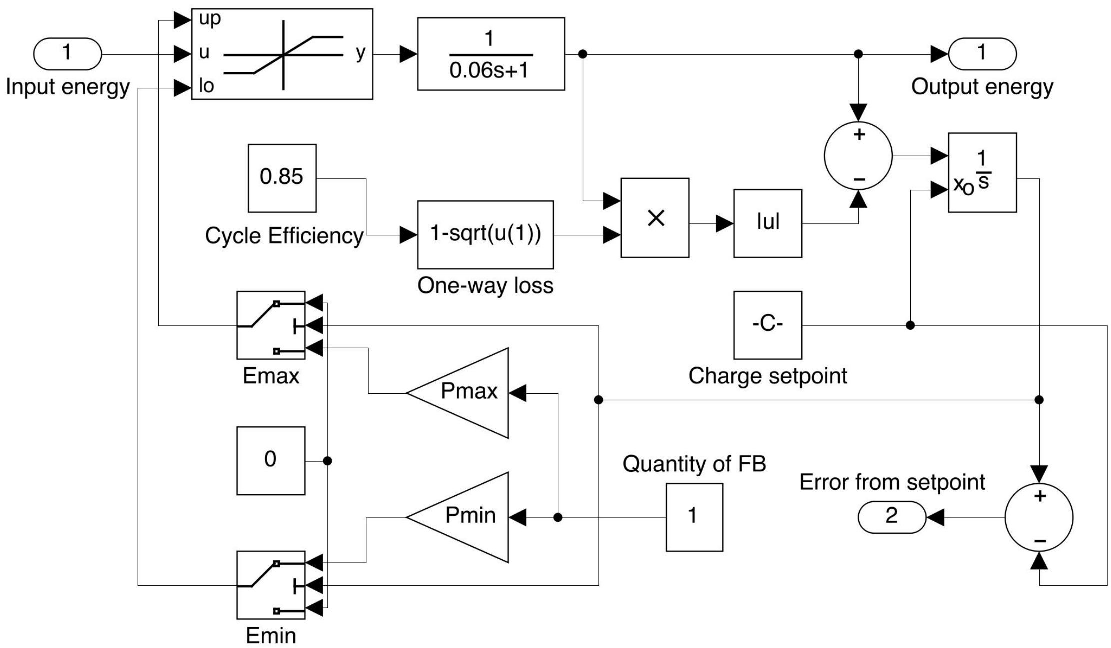

Fig. B.4 The structure of the flow battery model

Also, the relative cycle losses are equally divided into charging and discharging losses using the following formula:

$$\eta_{one-way} = \sqrt{\eta_{cycle}}, \tag{B.3}$$

$$L_{one-way} = 1 - \eta_{one-way}, \tag{B.4}$$

$$L_{one-way} = 1 - \sqrt{\eta_{cycle}} \tag{B.5}$$

where, $\eta_{one-way}$ is the efficiency of charging or discharging of the battery , η_{cycle} is the total cycle efficiency and $L_{one-way}$ are the losses associated with either charging or discharging of the battery.

Some assumption were made while designing dynamic model of the flow battery:

- The total efficiency of the flow battery cycle is $\eta_{cycle} = 85\%$ [TBH+09],
- The inertia time constant is 0.06 s (considering inertia of power electronics) [Con07],
- The total discharge of the flow battery is allowed ($E_{min} = 0$) [YZC09].

B.1.3.3 Model of Hydro Power Plant

A hydro turbine was used to compensate most of the system imbalance. The turbine output power follows the load variation trend from the forecasted value and aims to reduce the error. It also compensated the losses associated with the FB (see Section B.1.3.1). It was modelled using traditional governor controller/regulator commonly used in literature and transfer functions [KBL94]. In particular, a transfer function of hydro turbine is shown in (B.6). The rest of the hydraulic turbine and speed regulator model parameters are given in Table B.1. These parameters are chosen to match Kruonis hydro pumped storage power plant in Lithuania.

Table B.1 Parameters of the Turbine

Parameter	**Notation**	**Value**
Permanent droop	R	0.06
Temporary droop	r	0.5
Temporary droop time constant	T_r	0.5 s
Auxilary servo motor time constant	T_f	0.2 s
Gate servo motor time constant	T_g	0.2 s
Water time constant	T_w	4 s

The following traditional transfer function of the hydraulic turbine was used in the model:

$$\frac{\Delta\overline{P_m}}{\Delta G} = \frac{1 - T_w s}{1 + 0.5 T_w s} \tag{B.6}$$

where, $\Delta\overline{P_m}$ is the change in turbine mechanical power, ΔG is the change in gate position, and T_w is the water time constant.

The power to be balanced by the HPP is calculated using the following equation:

$$P_{HPPin} = (P_{error} + PID_{out}) \times \frac{1}{T_{LPF} s + 1} \tag{B.7}$$

where, P_{HPPin} is the power to be balanced by the HPP, P_{error} is the initial power imbalance, PID_{out} is the output from the PID controller and the T_{LPF} is the time constant of the LPF.

B.1.4 Investigation of Wind Power Imbalance

B.1.4.1 Research of the Optimal LPF time constant

The actual data of wind farms installed in Lithuania was used in this research (Fig. B.5). In particular it is the data of the forecasted and the actual wind power on the 27th of March 2012. The total installed capacity at that date was about 200 MW. The data was taken with the permission of the national transmission system operator. The mean absolute percentage error (MAPE) of wind power forecast during the investigated period is 11.7 % with a standard deviation (SD) of 13.05 MW. A histogram of the initial errors can be seen in Fig. B.9, depicted in blue. It should be noted that during that day a fault occurred at 13:20 because of a failure in the transmission line. A sudden drop of 35 MW (from 126 MW to 91 MW) was experienced due to a disconnection of a wind farm. This fault dramatically increased the required FB power and capacity ratings.

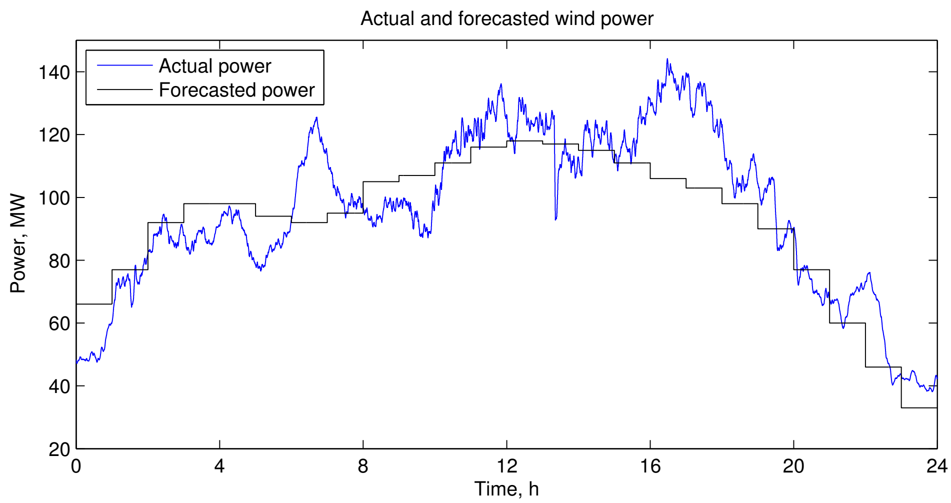

Fig. B.5 The forecasted and actual wind power

Due to high internal time constant of the hydro power plant and water inertia as well as rate limiting LPF it is not possible to fully balance the system (explained in Section B.1.3). That is why flow batteries are required after HPP in order to fully balance the total power by capturing high frequency fluctuation. A series of simulations have been run to acquire the relationship between low-pass filter time constant and the required FB capacity as well as the average rate at which the HPP input changes. Figure B.6 shows the results and the shaded region suggests the optimal operating region. The time constant has been chosen to be 300 s, which corresponds to a cut-off frequency of 530 μHz to be used in further investigation. It is an optimal choice because the average rate falls to a reasonable level of 18 kW/s and the required FB capacity stays in the feasible region from 1 MWh to 1.5 MWh.

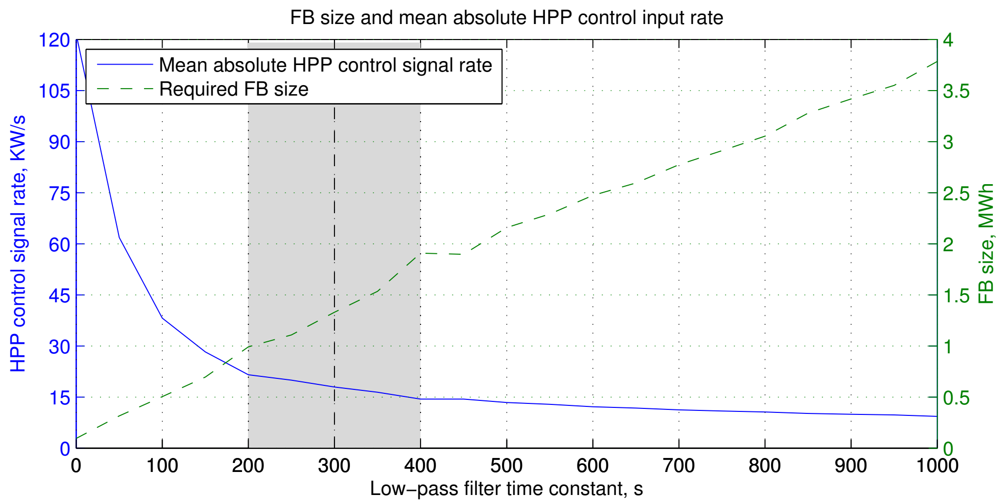

Fig. B.6 FB capacity and mean absolute HPP control input rate

In Fig. B.7 we can see the average charge and discharge rate of the FB. It also shows the average loss in power due to FB cycle efficiency. These values depend on the time constant of the LPF mentioned above and the shaded area shows the same optimal operating region where the mean power and losses are fairly low.

B.1.4.2 The Results of Proposed Balancing Technique

The simulations were run using the chosen optimal time constant of 300 s and the data from Fig. B.5. The results are shown in Fig. B.8. It includes the initial power system imbalance, difference after HPP, final imbalance as well as the operating power of HPP and FB. After the addition of HPP to the system, MAPE dropped to 2.45 % and SD to 3.22 MW. Figure B.9 shows the histogram of imbalance after the HPP in green. It should be noted that the mean over-generation of HPP is equal to mean losses in FB (about 180

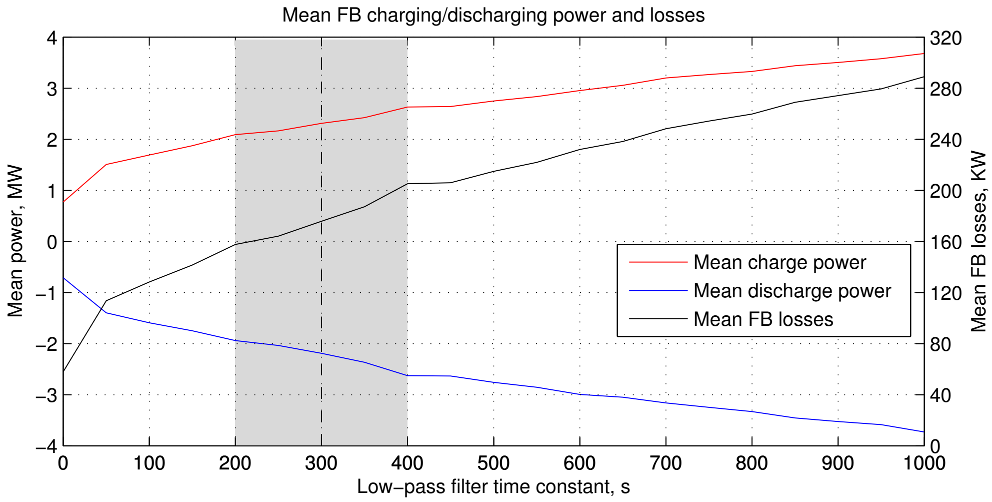

Fig. B.7 Mean FB charging/discharging power and losses

kW). This justifies the validity of the model. Overall, the addition of HPP gave positive results but further system balancing techniques need to be investigated.

The middle part of Fig. B.8 also shows a magnified portion of errors (between the time of 15:00 and 16:00) and it can be seen how the HPP power tracks the trend of the initial imbalance. On the other hand, the bottom part of the graph shows how FB follows the imbalance after HPP and the graph in red is the final imbalance (time from 15:30 to 16:00). The MAPE has now dropped to 0.087 % and the SD to 0.12 MW. A histogram of final imbalance can be found in Fig. B.9 shown in yellow. From the same graph it can be observed how the spread of imbalances decrease while propagating through the system.

During the investigation, the required power and energy of the flow battery was determined to be 33 MW and 1.33 MWh respectively. This is about 34 % of the mean wind power during the investigated period and about 16.5 % of the total installed wind power capacity in the Lithuanian power system (the total wind power is about 200 MW). A more detailed discussion on why the required FB ratings might be chosen lower, can be found in section B.1.4.3. Overall, these results can be considered as feasible for implementation.

Figure B.10 shows the charge level and accumulative losses in the FB during the simulated period. The required battery size is recorded to be 1.33 MWh. This is due to the failure in the system. If the event at time 13:20 is ignored, the required battery would be 0.93 MWh. That is 30 % less than the previous case. A super capacitor could potentially be used to serve the required ultra short term power.

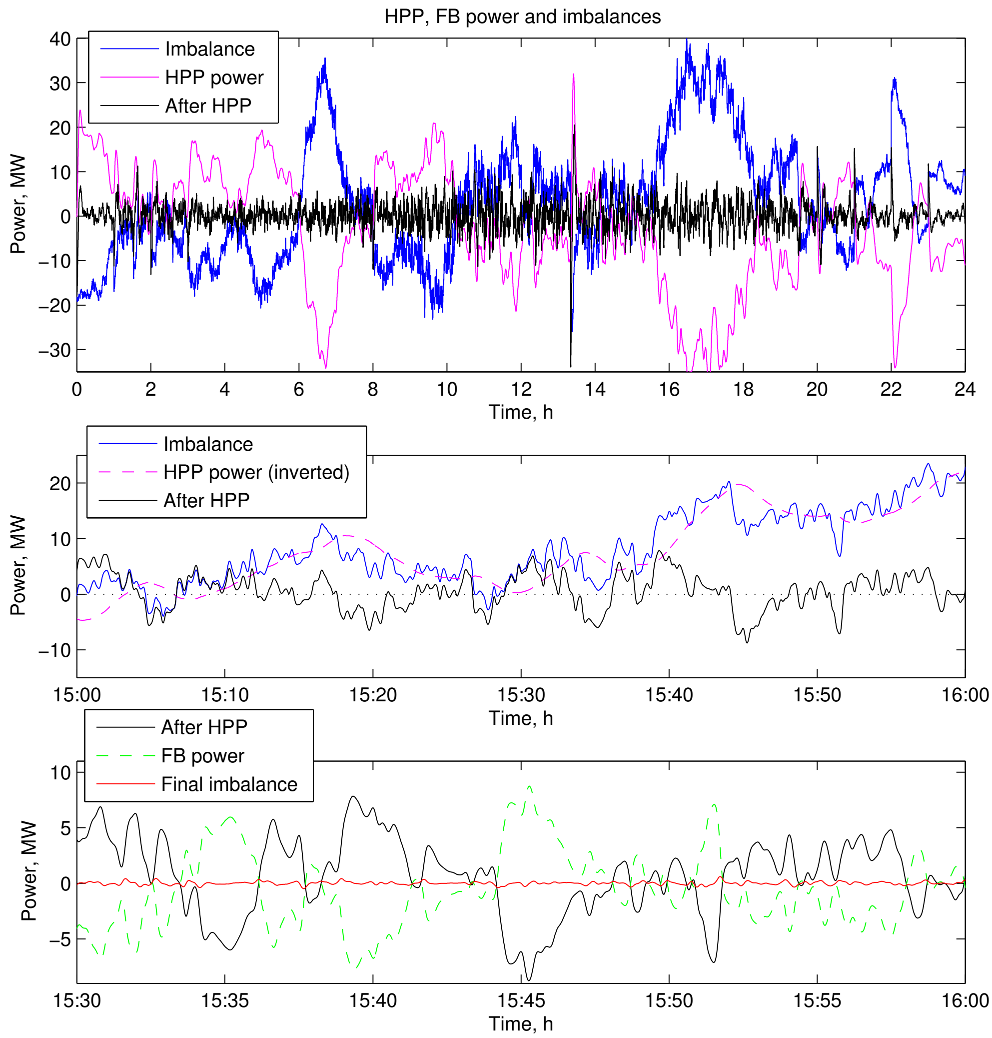

Fig. B.8 Balancing the difference between actual and forecasted wind power with hydro power plant

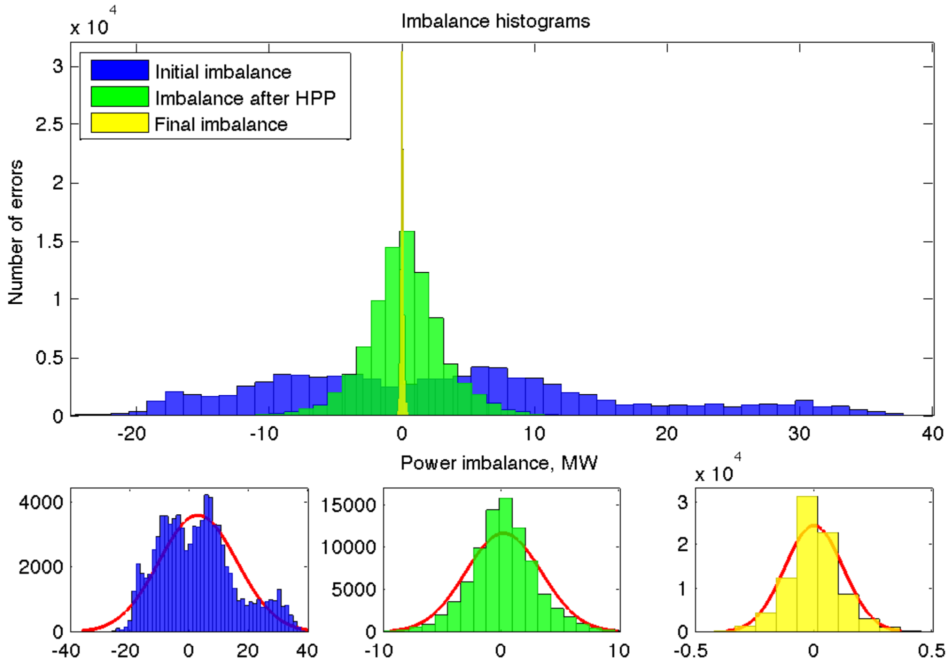

Fig. B.9 Histograms of imbalances at different points in the system

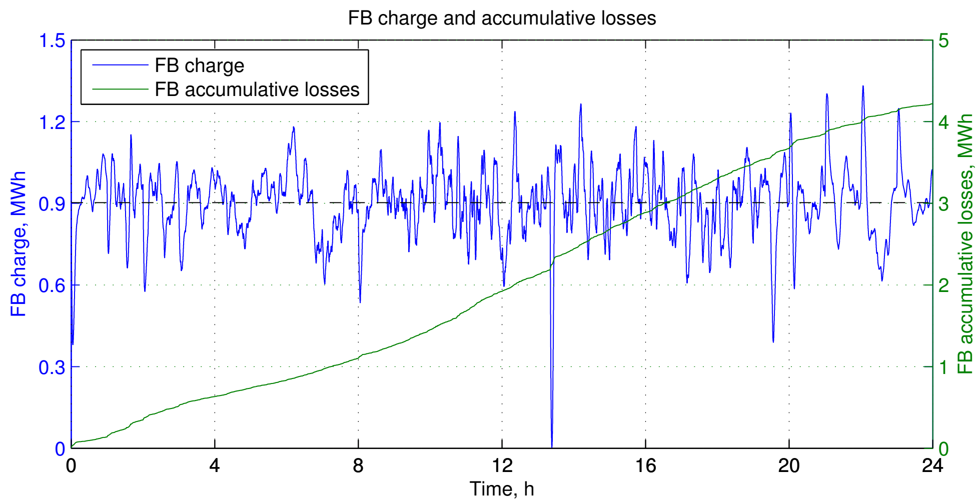

Fig. B.10 FB charge and accumulative losses

B.1.4.3 Limiting the Maximum Required FB Power

Considering the standard deviation of power to be balanced by the FB and the three-sigma rule it is reasonable to limit the installed FB power because high power is required during a negligible amount of time. This section discusses the trade-off between FB power rating and the final balance of power.

The data from simulations was extracted to calculate the balanced portion of energy depending on battery power and low-pass filter time constant (Fig. B.11). The color and isolines show the percentage of energy balanced using particular FB power ratings and LPS time constant compared to the energy captured by the FB without limits.

As it can be seen from Fig. B.11, the intersecting point of 300 s time constant and the 99 % energy balance iscurve corresponds to 16.7 MW maximum required power. That is a significant drop in the required FB power rating. The required capacity of the FB would also become 1.20 MWh. On the other hand, this limits the power required at the time of failure, which results in the increased final imbalance MAPE to 0.1 % and a SD to 0.4 MW.

A further decrease in energy capture could be considered. The 95 % would correspond to 7 MW FB power limit and 0.89 MWh required FB energy and would increase MAPE of final imbalance to 0.22 % and SD to 1 MW.

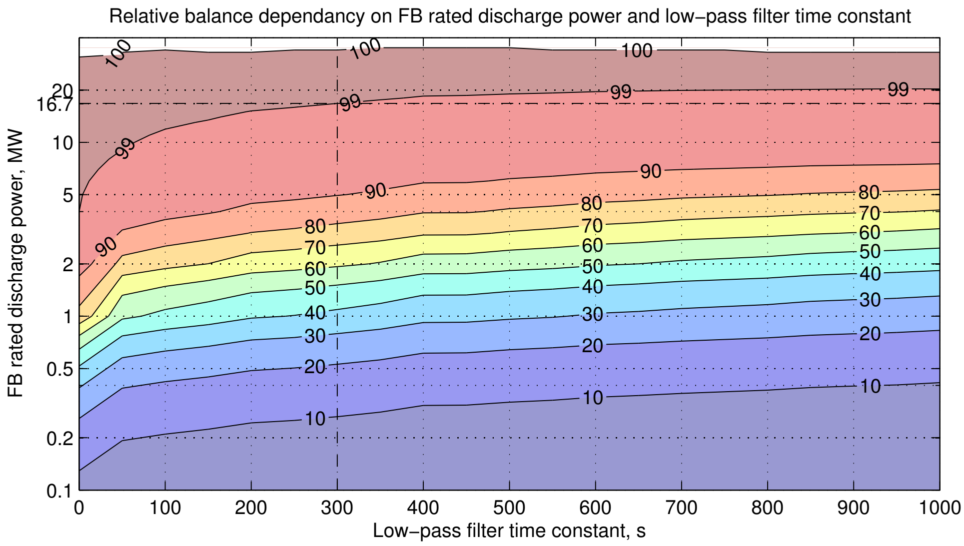

Fig. B.11 Relative balance dependancy on FB rated discharge and LPF time constant.

B.1.5 Conclusions

The proposed HPP and FB models and control strategy method gave positive results in balancing the wind power. It also generalizes the technique to find the optimal ratings of

Table B.2 Overview of Results (Imbalances)

Imbalance Stage	**Balance level (%)**	**FB rated power (MW)**	**FB cap. (MWh)**	**Statistical Measures**		
				MAPE (%)	**SD (MW)**	**ME (kW)**
Initial				11.67	13.07	3018.6
After HPP	100	33.0	1.33	2.45	3.22	180.7
				0.087	0.12	0.311
Final	99	16.7	1.20	0.101	0.40	-11.2
	95	7.0	0.89	0.221	1.00	-22.0

the flow battery in the Lithuanian power system. However this method could be applied to other electric power systems as well. It might be particularly important to PS which operate in island mode.

In this paper, a series of simulations were carried out to identify the cut-off frequency for the low-pass filter which optimally controls the power output of the hydro power plant. The optimal cut-off frequency identification enabled the estimation of the required flow battery power and capacity ratings. Also, the paper mainly focuses on the technical side of the method instead of looking at the economical value in detail.

After implementing the proposed control strategy for the HPP, the initial imbalance decreased about 5 times (from 11.7 % MAPE to 2.45 %). After introducing flow batteries, the system became fully balanced. However, it required FB size of 1.33 MWh and power of 33 MW. This constitute to about 16.5 % of the total installed wind power in the Lithuanian PS. Most of the FB power and capacity are required after short circuit in the overhead lines, which connect wind farm to the network i.e. power system emergency states. It should be mentioned that such ratings were required when covering every moment in time.

On the other hand, these events are relatively rare, besides some kind of flow batteries tolerate overloads for short periods without negative side effects. Making such assumptions the results of additional investigation showed that more reasonable flow battery ratings could be chosen. By covering 99 % to 95 % percent of the power imbalance, it is possible to reduce FB power rating by about 2-5 times and from about 10 % to 30 % in required FB capacity (Table B.2).

B.1.6 Future Work

Additional secondary power plants could be added (thermal power plant). Many other storage technologies could also be similarly modelled and investigated. In particular, high power and low capacity storage devices, such as super capacitors, could be added to compensate highest frequency imbalances thus highly improving the results and reducing power requirements for the FB. Having many different power plants in the model it is then potentially useful to research control strategies in order to reach for the highest economical or environmental benefit.

Another hot topic in energy storage and management field is the demand side management. In particular the interest focuses on HVAC system and water heater control in residential and commercial buildings. These systems could be used for load shifting (temporary storage and retrieval of energy). The potential efficiency of such balancing method might be very high.

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