

Analysis of Smart Grid and Demand Response Technologies for Renewable Energy  
Integration: Operational and Environmental Challenges

by

Torsten Broeer

B.Sc., Portsmouth Polytechnic, 1985

M.Sc., Carl von Ossietzky University of Oldenburg, 2004

A Dissertation Submitted in Partial Fulfillment of the  
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

in the Department of Mechanical Engineering

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## ABSTRACT

Electricity generation from wind power and other renewable energy sources is increasing, and their variability introduces new challenges to the existing power system, which cannot cope effectively with highly variable and distributed energy resources. The emergence of smart grid technologies in recent year has seen a paradigm shift in redefining the electrical system of the future, in which controlled response of the demand side is used to balance fluctuations and intermittencies from the generation side. This thesis investigates the impact of smart grid technologies on the integration of wind power into the power system. A smart grid power system model is developed and validated by comparison with a real-life smart grid experiment: the Olympic Peninsula Demonstration Experiment. The smart grid system model is then expanded to include 1000 houses and a generic generation mix of nuclear, hydro, coal, gas and oil based generators. The effect of super-imposing varying levels of wind penetration are then investigated in conjunction with a market model whereby suppliers and demanders bid into a Real-Time Pricing (RTP) electricity market. The

results demonstrate and quantify the effectiveness of DR in mitigating the variability of renewable generation. It is also found that the degree to which Greenhouse Gas (GHG) emissions can be mitigated is highly dependent on the generation mix. A displacement of natural gas based generation during peak demand can for instance lead to an increase in GHG emissions. Of practical significance to power system operators, the simulations also demonstrate that Demand Response (DR) can reduce generator cycling and improve generator efficiency, thus potentially lowering GHG emissions while also reducing wear and tear on generating equipment.

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DEDICATION

Dank seggen much ik min Öllern

Erna un Richard Bröer

dat se immer för mi dor ween sünd!

# Chapter 1

## Introduction

### 1.1 Motivation

Sustainability, climate change, increasing cost of fossil fuels and a political imperative for energy independence have combined to increase interest in the use of renewable energy sources to meet growing electricity demands, as well partially displacing existing thermal power generation. Current power systems are still dominated by fossil fuel based electricity generation and operated on supply following the changing demand. In such systems nuclear and coal plants usually operate as base load power plants, while other types of power plants, such as hydro and natural gas, balance the variability on the demand side. The increasing use of renewable energy resources adds additional complexity to power systems and makes them more challenging to operate, as illustrated in Figure 1.1.

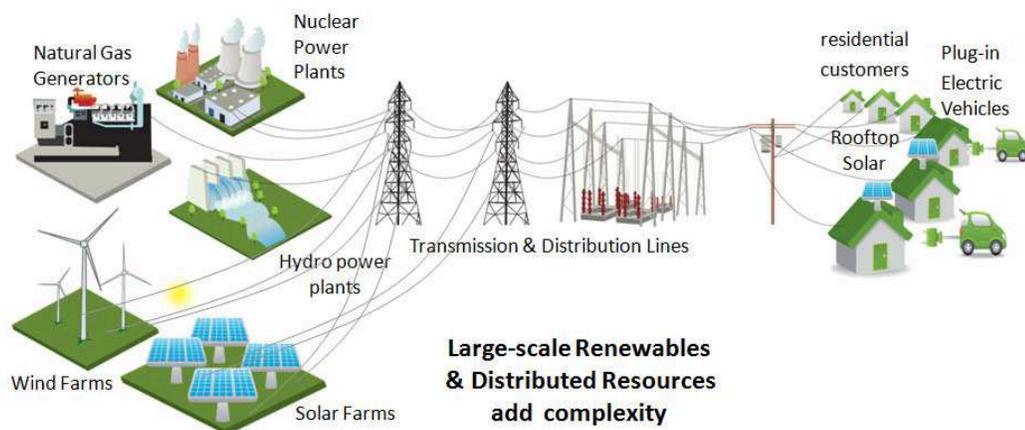


Figure 1.1: Power system overview

Renewable power generation resources can be divided into two groups:

- Those which have similar characteristics to conventional power generation facilities in that they are predictable and controllable. This group includes hydroelectric generation and the use of biomass.
- Those which are variable and intermittent, such as wind and solar.

This research will focus on Variable Renewable Energy sources, and in particular on the large scale integration of wind power into the electricity system. The displacement of fossil fuels by Variable Renewable Energy Sources (VRES) is considered to be a viable option for mitigating greenhouse gas emissions. However, compared with conventional power-generating facilities, VRES have challenging operating characteristics such as lower and more variable capacity factors and variable, intermittent availability. Figure 1.2 illustrates the extreme case of supply comprised of 100% wind power and the challenge of balancing a fixed and unresponsive demand with a variable supply.

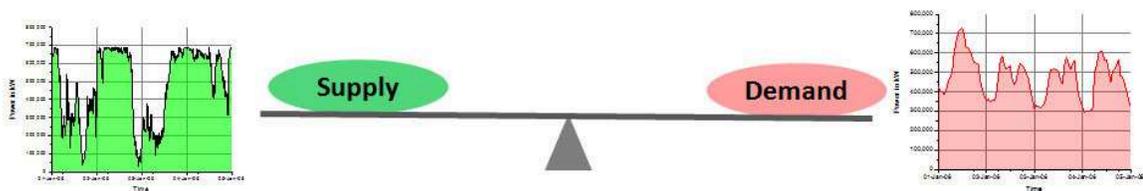


Figure 1.2: Balancing supply and demand

Superimposing demand and supply shows periods of both energy deficit and energy surplus (Figure 1.3). The traditional approach to making up for the energy deficit would be supply-side management by providing reserve capacity from other energy sources. However, the additional cost and infrastructure required could offset the economic and environmental benefits of utilizing wind power.

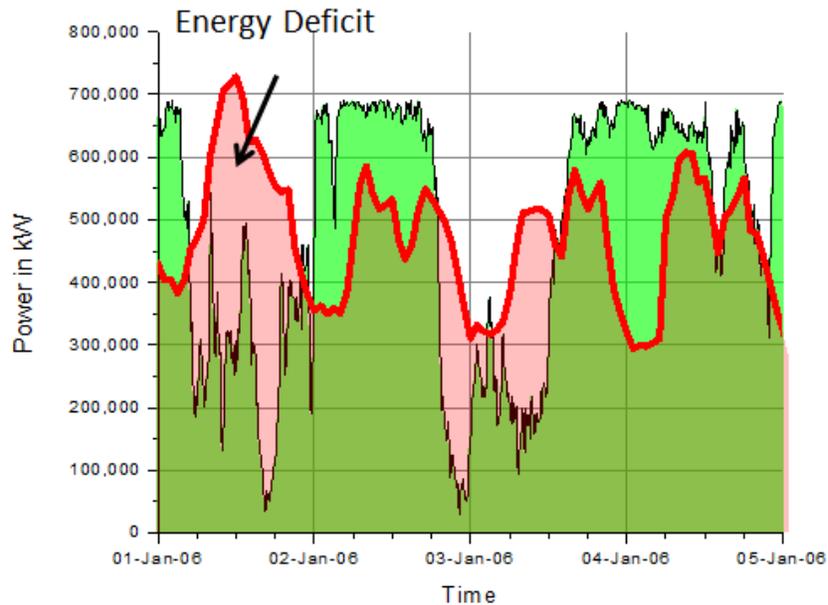


Figure 1.3: Energy deficit

The increasing penetration of wind power and other variable and distributed energy resources calls for an integrated system approach that includes not only supply side management, but also *the active participation of the demand side* in conjunction with emerging smart grid technologies. This thesis investigates a new approach to balancing electricity demand and supply by modifying the power consumption of residential loads in addition to the conventional way of balancing power by load following.

## 1.2 Literature review

Optimal operation of the electrical power system is a central objective in power systems engineering and includes the transmission and distribution grid, generation facilities and loads, and interconnections to other power system control areas. The overall goals are to reduce costs, improve overall system efficiency and ensure system reliability. Traditionally, these operational goals have been achieved mainly by managing the supply side (SSM) and by trading electricity, when available, with neighbouring power systems.

A simplified representation of an electrical power system is shown in Figure 1.4. It includes thermal, hydro electricity generation and VRES on the supply side, which have to match industrial, commercial and residential consumption on the demand side at all times.

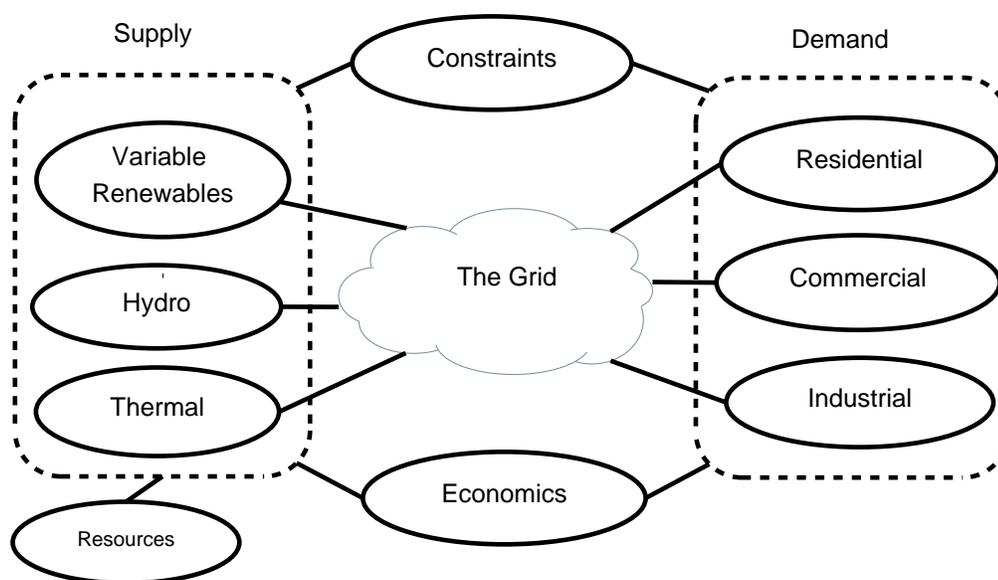


Figure 1.4: Aspects of an electrical power system

Today's power system is already complex and poses many challenges for system operators to ensure grid stability and reliability. The increasing integration of VRES, such as wind and solar power, adds further complexity and operational difficulties to the overall system.

This literature review covers the relevant work done to address these issues and concentrates specifically on the following aspects:

1. The need for more renewable energy

2. Renewable energy integration with an emphasis on wind power
3. Smart grid and demand response
4. Power system modeling

### 1.2.1 The need for more renewable energy

Climate change underpins much of the motivation for renewable energy. Mounting scientific evidence has led to the following observations and predictions:

- Although numerous and diverse factors contribute to climate change a major driver of global warming is the increase in atmospheric  $CO_2$  and other green house gases emitted by burning fossil fuels.
- Since the beginning of the industrial revolution the world temperature has increased by  $0.8^\circ C$  and the resulting melting of glaciers and polar ice caps has already led to a rise in sea level of 20 cm.
- $CO_2$  levels continue to rise and, without intervention, the temperature of the planet will rapidly reach what is considered to be the critical limit of  $2^\circ C$  above pre-industrial level, beyond which major ecosystems are predicted to begin collapsing.
- The International Panel on Climate Change (IPCC) predicts that a "business as usual" policy will risk a rise in global temperature of more than  $5^\circ C$  by the end of the century, with devastating consequences for the world's economy.
- A world-wide effort is necessary to reduce GHG emissions and prevent a looming climate catastrophe.

The introduction and expansion of renewable energy resources to replace fossil fuels, coupled with energy conservation initiatives, are the main pillars of a long-term strategy to achieve the required mitigation of GHG emissions necessary to minimize global warming.

### 1.2.2 Renewable energy integration

The balancing challenges introduced by variable renewable resources are addressed in a report from the IEA (International Energy Agency)[30], which also discusses pathways for "managing power systems with large shares of variable renewables". The variability and uncertainties of VRES increases the need for a flexible power system as shown in Figure 1.5.

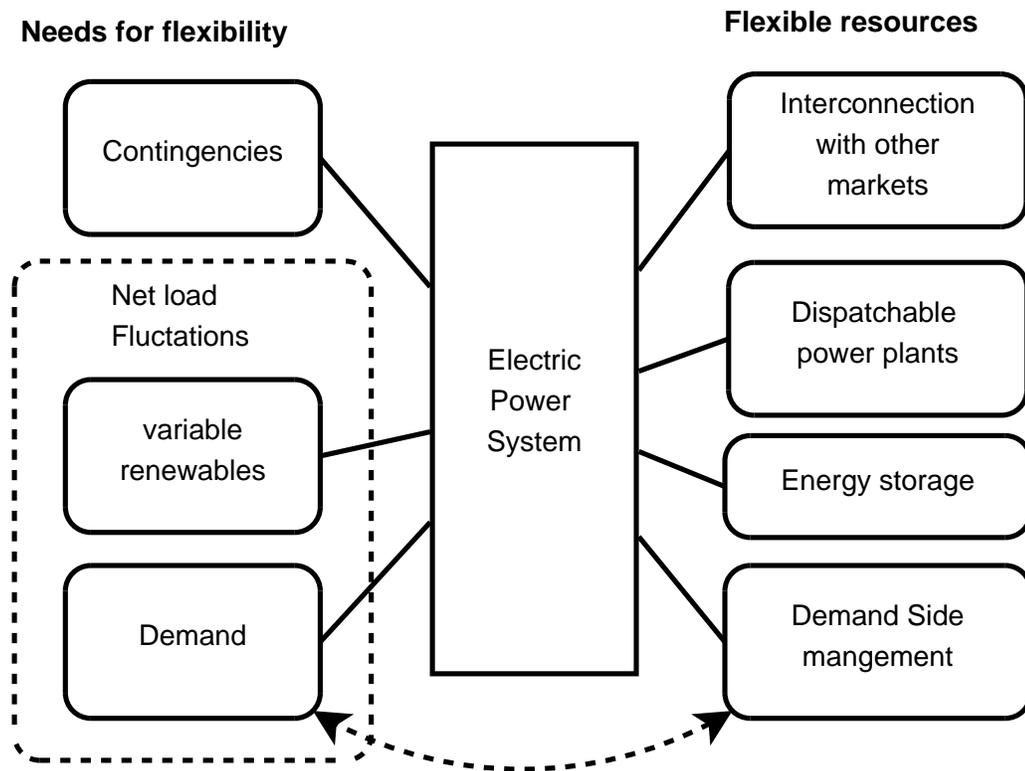


Figure 1.5: The need for flexibility

### Wind power integration

According to the wind energy roadmap from the IEA [31] the worldwide installed wind energy capacity is expected to grow from 464 GW in 2013 to 1403 GW in 2030. According to the same source wind power generation cost range from \$60/MWh to \$130/MWh and can already be competitive.

However, development of wind power plants requires land with sufficient wind resources. Proximity to the power grid is an asset, but often wind generation sites are remote from existing transmission lines and load centres. Public opposition due to

visual impact and noise, regulatory requirements and other environmental concerns are additional factors to be considered. Although wind energy fed into the power system has the potential to reduce reliance on traditional energy resources and reduce emissions, it may necessitate complementary power generation to balance the inevitable fluctuations in generating capacity. The additional infrastructure could offset the intended environmental and economic benefits. The optimal placement of wind turbines is thus influenced by a combination of socio-political, environmental, technical and economic factors.

An overview of integration of wind power into the power system as well as current approaches for assessing the technical and economic impacts of large scale wind power integration are investigated in [1]. Also included are the different methodologies used and definitions of common terms.

### **Wind integration studies**

Several relevant studies were analyzed by the IEA Wind R&D Task 25; these were compiled in the final report [27] published in July 2009. A summary paper emphasized the difficulty in comparing the results from the various studies. Factors such as the different assessment methodologies, time scales, input data and the different usage of common terms can lead to misleading interpretation of the results. Wind integration costs can vary widely and depend upon control area characteristics such as size, generation portfolio mix, the level of interconnections, the geographic dispersion of wind resources, level of wind penetration, system reliability and reserve requirements.

### **Methodology for modeling wind power impacts**

Modeling plays an important role in wind integration studies and both the parameters selected and methods used influence the results. The various modeling approaches are discussed and categorized in [42] to facilitate an understanding of different approaches.

A summary of modeling approaches impacting wind integration studies is presented in Figure. 1.6. This illustrates that different methods and assumptions lead to different results and conclusions. The ideal overall simulation method should include all the different cases (items) and input data. Ideally the factors listed in the shaded areas should be combined within a single model. However, due to current computational power limitations this is impractical so approximations and assumptions have to be made.

Item		1	2	3	4	5
A	Aim of study	What happens with X GWh wind	How much wind is possible			
M	Method to perform study	Add wind energy	Wind also replaces capacity	Optimal system design		
I	Imbalance calculation	Only wind	Wind + load	Wind + load + production		
B	Balancing location	Dedicated source	From the same region	Also outside region		
G	Grid limit on transmission	No limits	Constant MW limits	Consider voltage	N-1 criteria	Dynamic simulation
U	Uncertainty treatment	Transmission margins	Hydro inflow uncertainty	Wind forecasts: U3: no U4: persistence U5: best possible	U6: load forecasts considered	U7: thermal power outages considered
H	Hydropower modeling	Head height considered	Hydrological coupling included	Hydrological restrictions included	Availability of water considered	
T	Thermal power modeling	Ramp rates considered	Start/stop costs considered	Efficiency variation considered	Heat production considered	
W	Wind power modeling	Few wind speed time series	Many wind power time series	Time series smoothing considered	Allow controllable wind power	
S	Simulation model of operation	Deterministic simulation, one case	Deterministic simulation several cases	Stochastic simulation several cases		
R	Resolution of time	Day/week	Hour	Minute/sec		
P	Pricing method	Costs of fuels, etc.	Prices for trading with neighbours	Market actor simulation	Market dynamics included	
D	Design of remaining system	Constant remaining system	Optimised remaining production	Optimised remaining transmission	Perfect trading rules	

Figure 1.6: Methodology and input data for modeling wind power impacts

### 1.2.3 The smart grid and demand response

Today's electricity system has often been described as the "greatest and most complex machine ever built" [21]. While this system is complex, it is not smart. It is still a highly mechanical system of transmission towers, transmission and distribution lines, circuit breakers and transformers, the components of which were designed in some cases a 100 years ago. There is limited use of sensing, monitoring, communication and control devices throughout the overall system. In recent years a redesigned power system, often referred to as a "Smart Grid", has been proposed. It addresses the increasing challenges to the power system and offers potential solutions.

Smart grid is a term used to cover a broad spectrum of subjects; some are outside of the scope of this thesis, but are briefly noted with a few references below.

- Communication [23]
- Sensing and measurement [25]
- Standardization [34]
- Regulatory issues [47]
- Cyber security [46]

The pathways to a smarter grid are outlined in [9, 21, 13, 8] and include discussion and status assessment of information and communication technology as well as sensors, monitoring, and control. It is assumed that smart grid "technology will transform a centralized, passive power system into one that is dynamic, interactive, and increasingly customer-centric" [18]. Some smart grids concepts have already been implemented and tested in several projects, such as the Olympic Peninsula Smart Grid Demonstration Project [26, 6].

The benefits of a prospective smart grid have been investigated in several publications [39, 44, 15] and include technical, economical and environmental performance improvements in comparison to the traditional power system.

## History and definitions

The idea of influencing the electricity demand of customers is not new. DSM measures had already been discussed during the energy crisis at the end 1970s and shortly afterwards some of them were implemented [23]. Commercial and industrial customers were the main targets, and incentives were provided to reduce and change their electricity consumption when required.

The term DSM first appeared in the literature in the early 1980s. It referred to different strategies for managing loads rather than supply. A overview of various load control strategies is presented in [22] and were divided into load shape changes and load level changes as shown in Figure 1.7. Even at this early stage the vision included flexible load shape that later evolved into the "smart grid" concept.

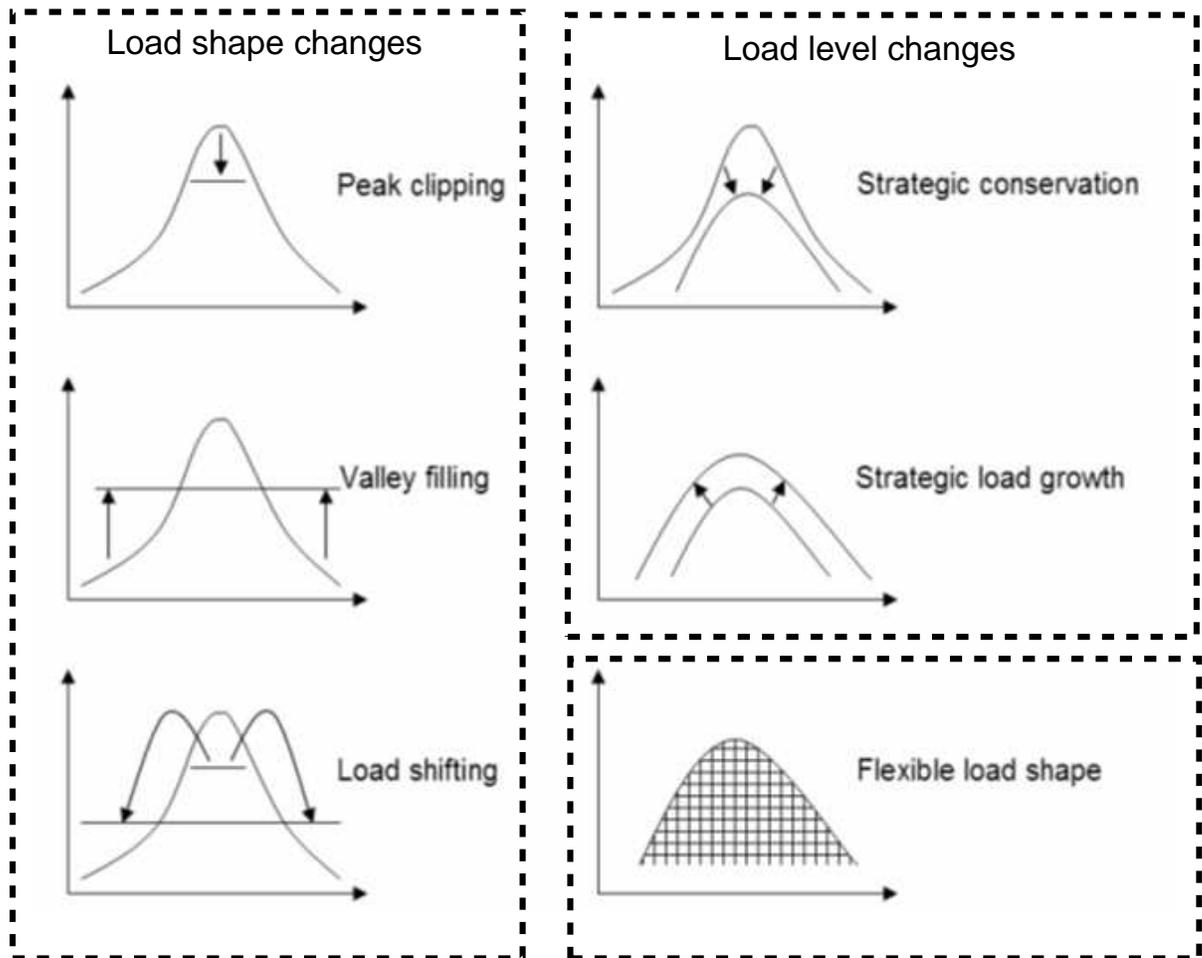


Figure 1.7: Load control strategies; adapted from [22]

## Demand response

According to the U.S. Department of Energy (DOE), demand response (DR) is defined as:

”Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.”

Changing the electricity usage of consumers can be translated into three implementation strategies:

1. Consumers are on call to reduce their usage when the grid is stressed. This requires predefined contracts between consumers and the utility company, the ability of Direct Load Control (DLC) and, preferably, knowledge about the state of the load. An important issue regarding DLC is that of consumers’ acceptance, as they may lose control of their energy usage [14].
2. Consumers have the option to react to certain tariff structures such as Time of Use (TOU). This may require both smart metering and installation of appliances controllers on the consumer side, in order to make this strategy a reliable DR resource.
3. Consumers have the ability to react to electricity prices within a Real-Time-Pricing (RTP) electricity market. This also would require enabling technologies, such as appliance controllers.

The question ”How to Get More Response from Demand Response?” has been addressed in [38]. This paper identifies enabling technology that utilizes fast, reliable, automated communication, that is critical for the effective implementation of DR. It also argues that having competitive markets with DR would have significant economic and political ramifications.

Electricity markets and the different pricing mechanisms are also discussed in [14]. The author promotes Demand Side Integration (DSI) for integrating flexibility and controllability into power system operations. Incentive- and price-based demand response strategies [2] are discussed, where either customers respond directly to price

signals (a market led approach), or a system operator (aggregator or agent) sends signals to the demand side customers. The author indicates that small consumers are ready and willing to participate in active demand, especially as the practice of TOU pricing component is already in place and accepted. However, the level of automation is important for both user comfort and demand response benefits.

### 1.2.4 Power system modeling

The requirements for modeling and analyzing energy systems are manifold and may include factors such as technical, economical, environmental and social aspects. This section reviews the current approaches to power system modeling and the transitions required to model both a smarter grid and demand response.

A comparative study ”of 13 of the most widely used PC based interactive software packages in the field of power engineering that are used for industrial applications, education and research” was conducted in [29]. The author defines four criteria, which he believes are essential for the software packages to be effective education/research tools. These criteria are:

- Allow network modeling through per unit representation
- Provide the behavior of networks under steady-state and transient conditions
- Allow for control of the network for economy/security conditions
- Have similarities with energy management systems used in control centres

Additional important criteria include factors such as an open architecture, expendability via a ”built-in toolbox” and an interface to other systems and libraries. It has been found that most of the software systems (e.g. PowerWorld) were strong in analyzing and optimizing AC power flow, but were not capable of dealing with renewable energy systems in a detailed manner.

### Agent based modeling

Requirements for a more intelligent power system design necessarily demand new electricity system models that go beyond the traditional approaches used for power system modeling.

A number of Agent Based Models (ABM) have been proposed as a better way to investigate electrical power systems in terms of power market interaction, grid congestion and environmental issues and are discussed in [41, 16, 7, 49, 35]. ABM, such as GridLAB-D or Electricity Market Complex Adaptive System (EMACS), represents the power system with multiple and diverse participants (agents). Each of the individual agents follow their own objectives, bidding strategies and may have the ability to learn from past experiences and adapt their behavior.

### **Load modeling**

It has always been of value to predict demand in order to schedule generation facilities and operate the electrical power system. Load modeling has usually been based on aggregated metered data from residences, commercial buildings and industrial consumers [4, 32]. This data-based modeling approach led to a relatively precise prediction of aggregated demand such as that of the electricity usage of residential houses.

However, with the introduction of the smart grid concept more detailed load modeling approaches had to be developed. Modeling now had to incorporate and vary the behavior of individual appliances (e.g. thermostatic loads) and include appropriate control strategies to achieve the desired demand response outcomes [50].

### **1.2.5 Summary of literature review**

This literature review provides a synoptic overview of the state of the art:

- The challenges and approaches of integrating large scale variable renewable energy sources into the electricity system.
- An overview about smart grid and demand response
- Power System modelling approaches and load modelling

The review identified the following open questions: What approaches are suitable for modeling and simulating a smarter grid in order to facilitate further investigation and understanding of the operation and interaction of individual loads, generators, markets and controllers within an overall system context? This thesis will especially focus on modelling and validating of such a system, and on the requirements and implementation of proper market operations including load and generator bidding.

Furthermore a new methodology for emission tracking and a procedure that accounts for generator cycling will be introduced.

### 1.3 Objectives

The overall objective of this research is to determine whether residential loads within a smart grid architecture can support the integration of wind power. While various types of residential loads can potentially mitigate the negative impacts of the variability of wind power, this research focuses on using only one type, space heating, as a demand response resource. The more specific objectives are to:

- Create and validate a smart grid model
- Superimpose wind power on the model and show qualitatively, how demand responds to power surpluses and deficits
- Quantify the impact of a smart grid on the potential reduction of green house gas emissions
- Quantify how demand response influences generator cycling when wind power or other variable generation contributes to the electricity generation system

### 1.4 Methodology

This thesis proposes a new approach to balancing demand and supply by managing residential loads instead of the traditional method of adding generating capacity to match demand. A smart grid power system model was designed and then validated using actual performance and temporal data from a physical experiment: the Olympic Peninsula Demonstration Project. Wind power generation was then superimposed on the validated model. The model incorporates suppliers and demanders who bid into a real-time pricing (RTP) electricity market. The methodology focuses on the utilization of selected residential end-use appliances with an intrinsic storage capacity (thermal loads), that are able to alter their power consumption with minimal effect on the comfort of the consumers. Loads become responsive and reduce or increase their consumption depending on both their power needs and current electricity prices. A surplus of power will result in a lower market price and appliances will respond by

switching on or staying on. Deficits of power will result in a higher market price and as a consequence appliances will switch off or stay off. Within this double auction electricity market, these responsive loads behave as additional grid resources.

## 1.5 Contributions

This research contributes to the development of smart grid system modeling methodologies that allow the investigation and analysis of large scale wind energy integration into the electricity system.

We make *four* claims that are validated in my dissertation:

This work on smart grid modeling and demand response explores and quantifies pathways to mitigate the problems associated with wind power integration and includes the following outcomes, whose practical applicability are demonstrated through validated simulations:

1. Creation and validation of a smart grid model.
2. Identification of the benefits and challenges of demand response.
3. Quantification of the mitigation of GHG emissions.
4. Quantification of the mitigation of generator cycling.

# Chapter 2

## Modeling and validation

### 2.1 Introduction

Modeling the electrical power system presents many challenges because it involves the representation of several subsystems and their interactions, including the generation side, the demand side, electricity markets, and the transmission and distribution system. In addition there are many constraints to take care of, such as voltage and frequency limits and line capacities. With the transformation of the current electricity system into a smarter grid this modeling task becomes even more complex, especially as loads now become an active part of the overall power system, and hence a detailed knowledge about their behavior is also required. The questions are:

1. How do loads behave?
2. How can their behavior be altered?
3. Do the loads exhibit the desired behavior?

This chapter will describe the overall system modeling approach adopted in this thesis and its validation.

### 2.2 Model system description and grid modeling

An agent-based modeling environment was utilized for modeling a smart grid power system using the open source GridLAB-D<sup>TM</sup> simulation platform [10]. This general modeling framework includes a range of models and sub-models, accounting for loads ,

market, distribution and transmission system, end-use and their coupled interactions within the overall system. The variety of component models within GridLAB-D<sup>TM</sup> and the array of user determined parameters and variables allows comprehensive modeling and simulation of a variety of complex electric power systems and scenarios, and makes this platform particularly well suited to exploring the integration of new energy technologies. Additionally no open literature studies [33, 17, 37, 36] include detailed load modeling within an overall system context and therefore GridLAB-D<sup>TM</sup> was selected for this study. The application of the model to solve the power flow problem within a 3-phase unbalanced system utilizes the Three-Phase Current Injection Method (TCIM) [20] for specific transmission and distribution scenarios.

This section focuses primarily on two general aspects of the system model that have been further developed as part of this thesis: market modeling and generator modeling. The system and component models were developed within the GridLAB-D<sup>TM</sup> modeling environment. MATLAB was utilized for pre- and postprocessing of data and for generating some of the GridLAB-D<sup>TM</sup> macro codes.

### 2.2.1 End-use load modeling

The electric end-use loads of any house can be divided into two major classes: non-thermostatic loads, have been such as lights and outlets, and thermostatic loads, such as Heating, Ventilation, and Air-Conditioning (HVAC) units, water heaters and refrigerators. Thermostatically controlled loads include some form of intrinsic storage, such as the thermal mass of the home or water in the tank. Therefore the loads service function will be maintained during power interruptions over a limited amount of time, without affecting user comfort.

HVAC systems and water heaters generally have a high potential for demand response, which depends on factors such as size of system and house, insulation, location, weather and the recent demand response history. Fig. 2.1 shows the average energy consumption for a single family residential house in the U.S., where space heating, air conditioning and water heating together account for 66% of the total energy consumption. Other household appliances, such as lights, have limited or no demand response potential as switching off these appliances would generally be not acceptable to customer and adversely effect their comfort.

The house model in Fig. 2.2 is based on the Equivalent Thermal Parameter (ETP) model. The ETP model determines the state and power consumption of the HVAC

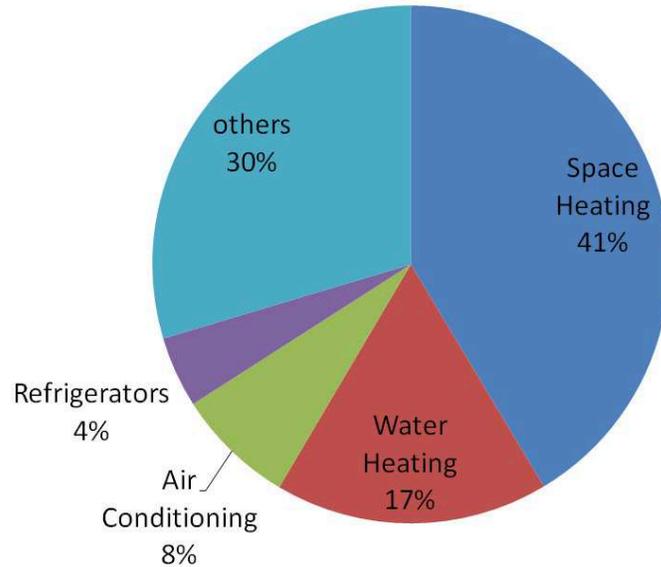


Figure 2.1: Average energy consumption for a single family house in the U.S.A (data source:[48])

system while also considering the heat gain through the use of other residential appliances, and heat gain/loss to the outside environment as a function of weather. Other household loads were integrated into this model using physical, probabilistic, and time-varying power consumption models. These models are all available within the GridLAB-D development environment [45, 5].

### 2.2.2 Market

Fig. 2.3 shows the bidding behavior of the controller of HVAC loads during heating mode. Every load controller observes the electricity market, and automatically places a bid for power that is influenced by the average market price and standard deviation, the market clearing price and the current state of the load, defined by the difference between the current and desired temperature. The bidding price formulation of the controller is given in Equation 2.1.

$$P_{bid} = P_{avg} + \frac{(T_{current} - T_{desired}) * k_{high/low} * \sigma_{act}}{|T_{max/min} - T_{desired}|} \quad (2.1)$$

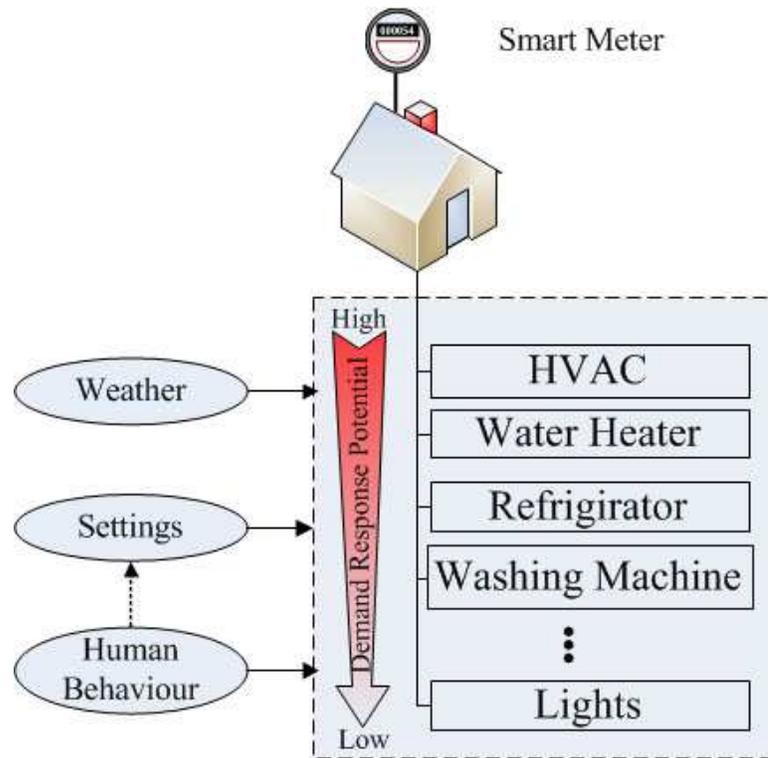


Figure 2.2: Residential house model: electrical appliances with varying potential for demand response are shown, along with other variables such as weather and human behavior.

where  $P_{bid}$  is the bid price below which the load will turn on,  $P_{average}$  is the mean price of electricity for the last 24-hour period,  $T_{current}$  is the current indoor temperature,  $T_{desired}$  is the desired indoor temperature,  $k_{high/low}$  are the predefined comfort setting,  $\sigma_{act}$  is standard deviation of the electricity price for the last 24-hour period,  $T_{max/min}$  is the maximum or minimum temperature range.

In this example, the upper and lower setpoints for the desired room temperature are  $22^{\circ}\text{C}$  and  $17^{\circ}\text{C}$  and the intelligent controller of the heating appliances places price and power bids into the market according to its power needs. A high room temperature results in a lower price bid, and no bid at all when the room temperature is  $22^{\circ}\text{C}$  or higher. A lower temperature results in a higher price bid with a maximum possible market price (cap price) when the temperature falls below the  $17^{\circ}\text{C}$  threshold set by residents as their minimum comfort level. A bid at the cap price ensures that the bid is always successful in purchasing power. Under this condition the load now behaves as an unresponsive load, as it is only bidding the fixed cap price into the market and purchases power at whatever the market clearing price might be.

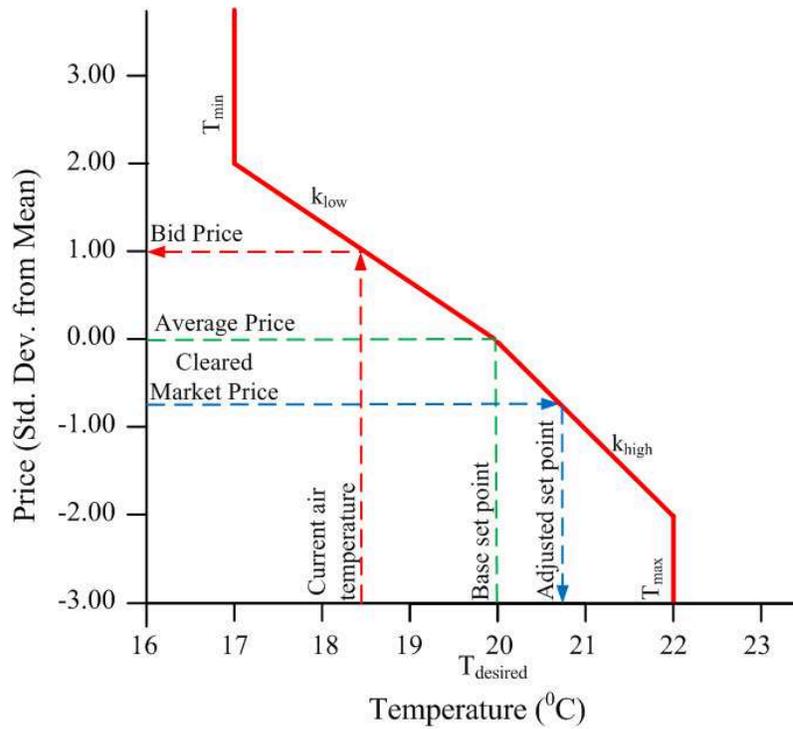


Figure 2.3: Bidding behavior of the controller of a thermostatic heating load set between 17°C and 22°C

The setpoints of the controllers are determined by the individual consumer and therefore the heating system of each house reacts differently depending on the consumer's desires for comfort versus money.

## 2.3 Case study: The Olympic Peninsula Experiment

The Olympic Peninsula Demonstration Project was conducted between April 2006 and March 2007 for the U.S. Department of Energy (DOE) and the Pacific Northwest GridWise<sup>TM</sup> Testbed under the leadership of the Pacific Northwest National Laboratory (PNNL). The project was undertaken to investigate how electricity pricing could be used to manage congestion on an experimental feeder. A Real-Time Pricing (RTP) electricity market with an interval of 5 minutes was established to facilitate more active participation of end-use appliances and distributed generation within the electricity system. A dynamic pricing mechanism was implemented, where suppliers and demanders offered bids into a common market. A simplified represen-

tation of the overall demonstration project is shown in Fig. 2.4.

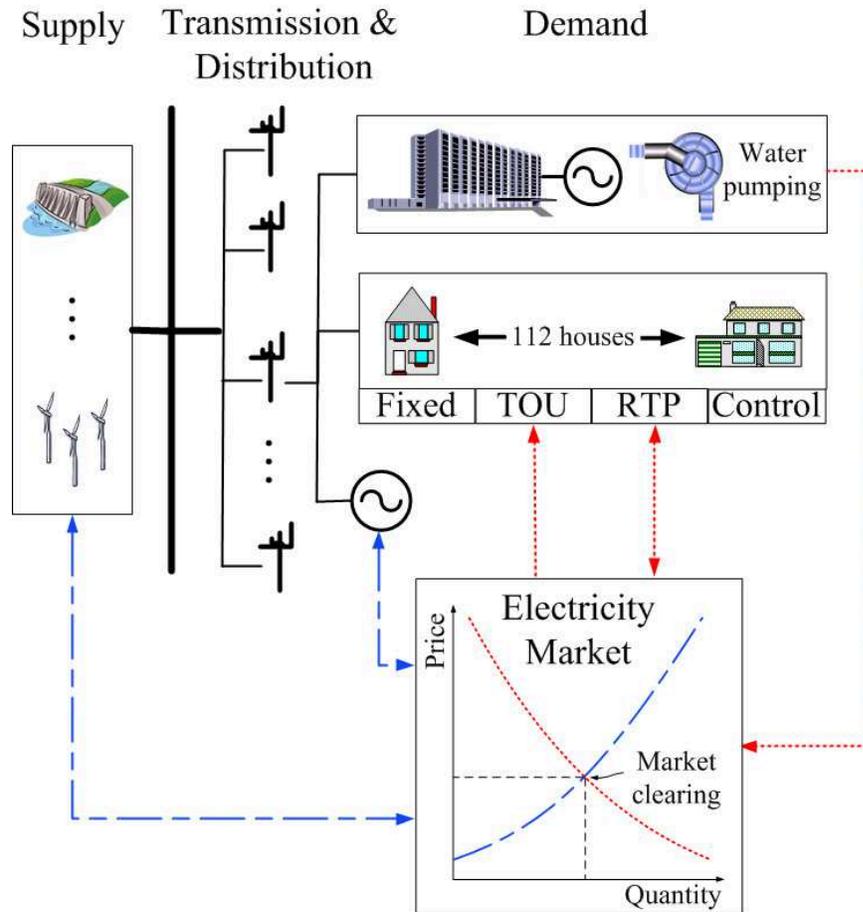


Figure 2.4: Overview of The Olympic Peninsula Smart Grid Demonstration Project, where different suppliers and demanders are part of a double auction real-time electricity market

One part of the demand side was comprised of a commercial building, backed up by two diesel generators of 175 kW and 600 kW. The building load represented a resource capacity and was able to place price and power bids into the market. Under certain market and bidding conditions, the building could effectively disconnect itself from the grid by transferring power generation to the diesel units.

Another part of the demand side resource consisted of 112 residential houses retrofitted with intelligent appliances capable of receiving and responding to price signals from the electricity market. This enabled a home to automatically change power consumption based on the current market price of electricity. The aggregate load when all the responsive devices are on is approximately 75 kW. Each partici-

pating house operated on one of three different types of electricity contracts: fixed, Time-of-Use (TOU) with critical peak price (CPP), and RTP. For comparison, an experimental control group of standard non-participating houses was included.

In addition to the commercial building and the residential houses, the project also included two municipal water-pumping stations. These two pumping stations offered about 150 kW of controllable load into the market.

The project demonstrated that, for a single experimental feeder, peak loads and distribution congestion could be reduced by enabling loads to interact within a market clearing process. More information about the Olympic Peninsula smart grid experiment can be found in [26, 6] and is presented in the system model that duplicates this experiment.

### 2.3.1 System modeling

This section presents a smart grid power system model replicating the supply, demand, distribution, transmission and market of the Olympic Peninsula Demonstration Project.

#### Transmission and distribution

The entire transmission system is modeled as a single slack bus feeding into the distribution system. The distribution grid model is based on the physical characteristics of the Olympic Peninsula Experiment (OPE).

This model presents an unconstrained transmission grid above the connection point of the feeder, capable of providing infinite power. However, the electricity market limits the supply so that the feeder capacity is effectively constrained to maximum capacity of 750 kW. This constraint represents a transmission line capacity limit of one of the supply lines to the Olympic Peninsula system.

#### Supply

The supply is represented by two entities. The first is bulk electricity from the Mid-Columbian wholesale market. For the physical model of the power system, this supply appears to have infinite capacity. However, the actual supply is controlled by market dynamics, where the power quantity supply bid from the Mid-Columbian (MID-C) market is always 750 kW at a wholesale price based on the MID-C electricity mix as shown in Fig. 2.5. This effectively constrains the feeder capacity to a limit of 750 kW.

The second supply entity is a micro-turbine that provides an additional distributed supply of 30 kW.

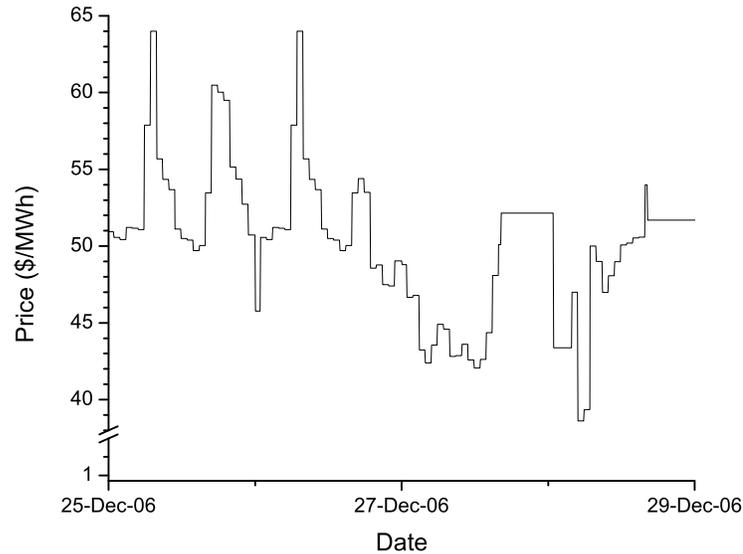


Figure 2.5: Variation in the Mid-Columbian wholesale electricity price over a four day period during December 2006

## Demand

The demand side in the OPE incorporates a variety of residential houses and a commercial building with back up generation. Appropriate and detailed load and house models are required to represent realistic system behavior. The following subsections describe the residential house model and a model of the backup generator for the commercial building.

One-hundred and twelve (112) individual residential houses are modeled using data extracted from the OPE. The data includes the size, type and thermal properties of houses, used appliances and occupancy mode. The weather, settings of the appliances and human behavior all have salient influences on the power system and are included within the system model Fig. 2.2. Different schedules and thermostat settings are used to reflect the various occupancy patterns, home heating and hot water usage that together represent the major responsive loads.

## Generator model

The commercial load with two back-up diesel generators is a unique feature to the Olympic Peninsula demonstration. If the market clearing price exceeds the building bid, the generators will turn on and effectively remove the building from the feeder system.

New generator controllers were developed to allow generators bidding into a wholesale or retail market. The generators bidding behaviors are characterized by the generator cost curve and include fixed cost, fuel costs, start up and shut down costs. The building bid is determined by the cost of producing power from its backup generators that represent a potential "negative load". Since the generators are diesel-fueled, yearly runtime allowances are a key component of the bid price formulation. Equation (2.2) includes the various parameters contributing to the bid price.

$$\begin{aligned}
 bid\_price = & license\_premium(fuel\_cost \dots \\
 & + O\&M\_cost + startup\_cost \dots \\
 & + shutdown\_penalty)
 \end{aligned} \tag{2.2}$$

where:

- license\_premium*: factor used to weight the bid price by the number of remaining licensed operation hours remaining in the year
- fuel\_cost*: fuel cost for running 1 hour
- O&M\_cost*: operating and maintenance costs per capacity-time
- startup\_cost*: projected penalties associated with starting the unit
- shutdown\_penalty*: projected penalties associated with a premature shutdown of the unit.

The basis and detail formulation of this equation are given in [26]. In particular, the *license\_premium* term includes the influence of yearly runtime restrictions and how many hours have been used by the plant to date. For example, if the generator

runs a significant portion of its hour limit early in the year, the remaining hours are ascribed a higher value since they need to “last” the rest of the year.

In the OPE, both generators were attached to the same building, allowing different portions of the building load to be switched from one generator to the other, as appropriate. However, to simplify modeling and simulation, two buildings were assumed, each with one generator attached to it.

## 2.4 Simulation, validation and case studies

This section explains the simulation and validation approach. It involved refining the model by calibrating the input data, and validating the simulation results by comparing them with actual data from the Olympic Peninsula Demonstration Project.

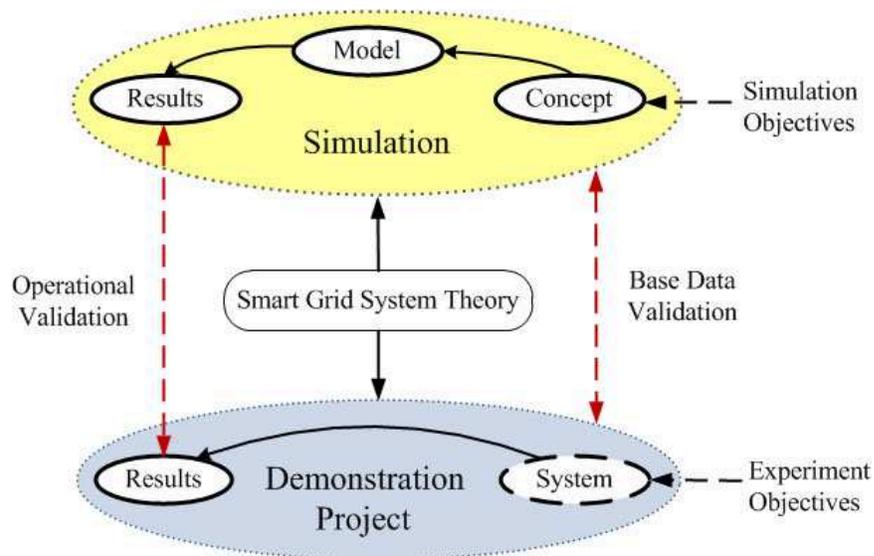


Figure 2.6: Validation approach: Comparison of base reference data and operational results from the demonstration project with the simulation

The last week of December 2006 was chosen as a reference period to run the corresponding simulation. Although the OPE extended over a period of one year; the simulations were restricted to this week, as it was the only week during the heating season with consistent and complete data. All reference data utilized are publicly available within the analysis section of the GridLAB-D website [24].

Given the complexity of the physical system and the intractability of resolving all the details and temporal scales, an exact reproduction of the field data is unrealistic.

Rather, the objective was to verify that model and demonstration project behavior exhibit similar characteristics. In order to determine the correctness of the model, the primary validation approach is based on data and operational representativeness of the model.

### **2.4.1 Base reference data validation**

Base reference data were extracted from the demonstration project and introduced into the model in order to create a physically representative environment in which to conduct the simulation. These data included weather, schedules, thermostat settings and the characteristics of all 112 individual houses. The setpoints and schedules for the HVAC and hot water system model reflected the effects of seasonal changes, such as winter and summer, and usage patterns for weekdays and weekends. Additional loads were represented as scheduled constant impedance, current and power (ZIP) loads [40]. These additional loads were divided into two categories: responsive and unresponsive loads. Unresponsive loads included appliances that would not respond to the market, such as lights, plug loads, clothes washers, clothes dryers, dishwashers, cooking ranges, and microwaves. Responsive loads are influenced by the market (like the HVAC and water heater explicit models) and include refrigerator and freezer loads.

### **2.4.2 Operational validation**

With the base reference data extracted and helping to define the basic physical aspects of the system, the behavior of these underlying systems needs to be validated. The behavior of the various load devices and the electricity market on the system were both validated to ensure similar behavior to the original OPE.

#### **Load validation**

After reproducing the base data of the demonstration project, the behavior of the aggregated load was tested and validated. First, the load behavior of both the fixed and control house groups was tested and validated. The load curve of each house is mainly influenced by weather and thermostat setpoints and schedules, which reflect human behavior, as illustrated in Fig. 2.2.

Fig. 2.7 shows the average power demand of houses in the control group over a 24-hour period. The actual behavior of houses in the Olympic Peninsula Demonstration Project are compared with the corresponding group from the simulations. Both exhibit similar characteristics with good overall agreement in power levels and ramp up/down rates, except for some discrepancy around  $T = 15$  hrs. Given the complex dynamics of the system, it is difficult to ascribe this to a particular component of the model. Although some of the discrepancy can be attributed to the small sample of houses and some of the scheduling mismatch, adjustments would at this stage be somewhat arbitrary.

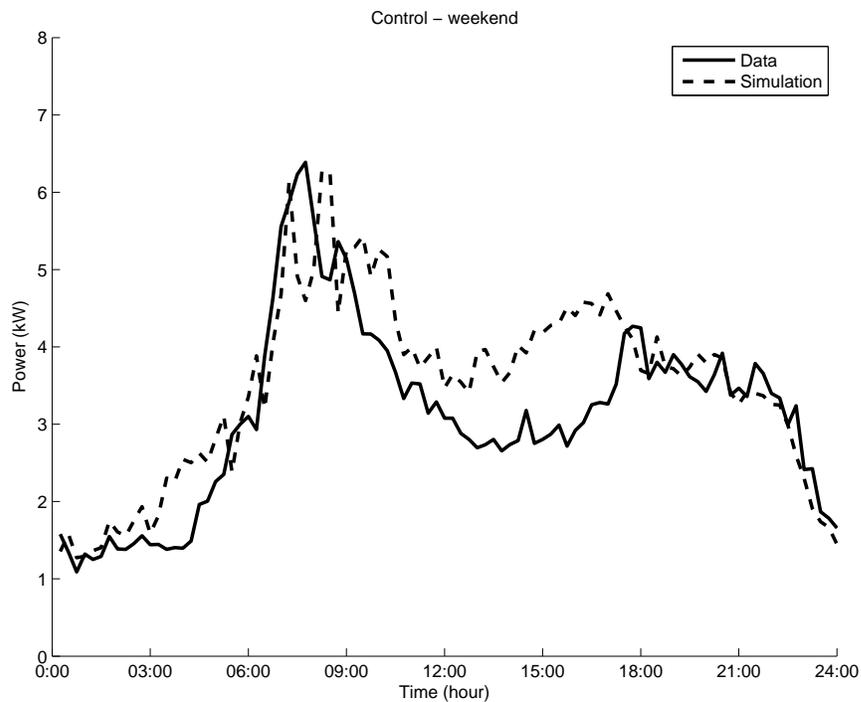


Figure 2.7: Comparison of simulation results with the demonstration project: Average power demand of all houses in the control group over a weekend 24 hour period.

Second, the load behavior of both the RTP and TOU house groups was tested and validated. Since the appliances in these houses were retrofitted with intelligent, price responsive controllers, it had to be shown that the appliances reacted appropriately to price signals. This involved feeding the market clearing prices from the OPE into the system model via time series data.

At this stage of the validation process, the loads reacted to the price data from the project by switching on or off without placing bids into the market. Fig. 2.8 shows

that the modeled houses with their controlled appliances show similar behavior in comparison to the real life experiment.

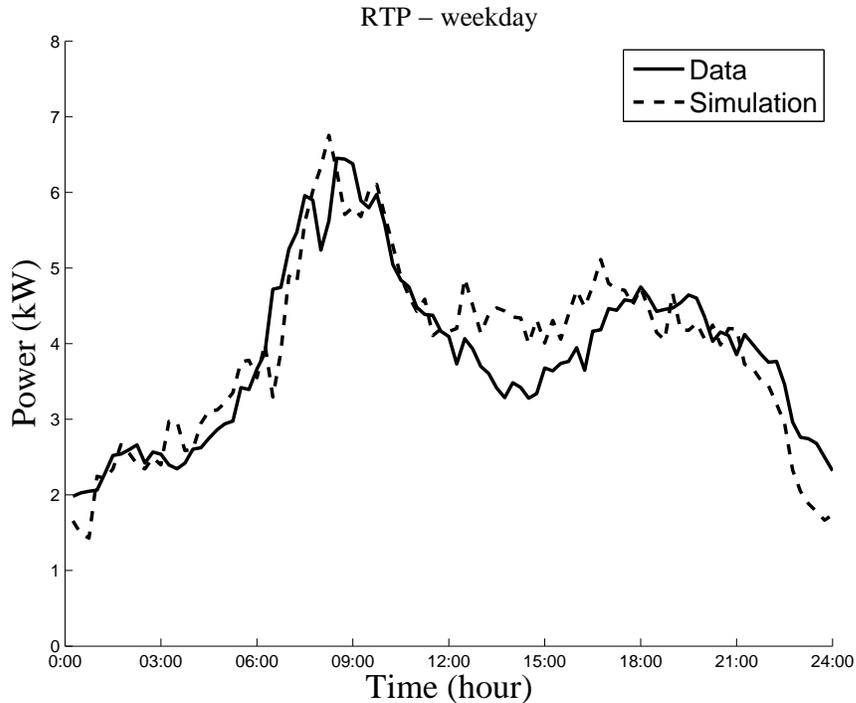


Figure 2.8: Comparison of simulation results with the demonstration project: Average power consumption of all houses in the RTP group over a weekday 24 hour period

### Market validation

In this section, the full market dynamics, including market pricing, were tested and validated. This involves a double auction RTP market, where the residential loads on RTP-contracts receive and place bids into the market. In comparison to the previous load validation process, the intelligent load controllers place their own bids into the market that depend on the state of the loads and the current market price.

In addition, commercial buildings place bids into the market by offering to switch off the total building loads. The bid price and quantity depend on the operating costs of the backup generators to produce electricity, as described in equation (2.2).

The market interaction between electricity suppliers and demanders are shown in Fig. 2.9. It illustrates one specific market event in the system. The market was updated every 5 minutes. The simulation time-step for buildings and appliances was set to 15 seconds as it must be significantly smaller than the market cycle time. This

ensures that the fidelity of load diversity is preserved, and prevents the loads from turning on and off simultaneously when the market cycles.

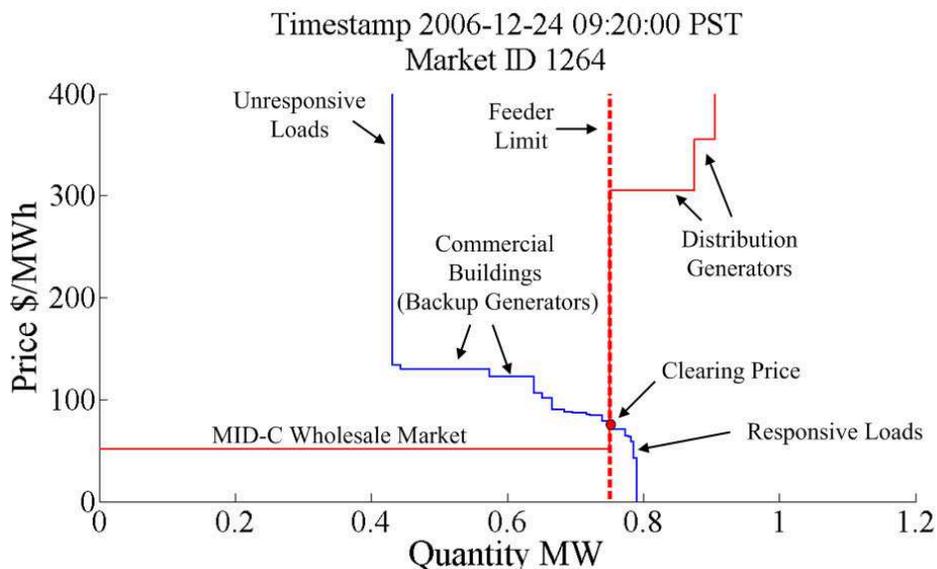


Figure 2.9: Market interactions

The substation supply is represented by the wholesale price obtained from the Dow Jones MID-C Electricity Index. This power bid is always 750 kW and is constrained in order to mimic the feeder limit. The bid price varies according to the price fluctuations shown in Fig. 2.5.

A 30 kW micro-turbine is the second seller and bids its maximum capacity with a varying price into the market. The micro turbine is located downstream of the feeder, and therefore the total available supply capacity exceeds the feeder limit by 30 kW.

The commercial building always bids its corresponding load into the market at a price that is equal to the cost of running the backup generators. If the market clearing price exceeds the bid price, then the backup generators turn on and the building removes itself from the grid. This is the reason why the generator capacity appears on the demand side.

On the pure demand side, houses that are on the RTP tariff bid into the market. Depending on their power needs, the power and price bids vary for each participating house. The houses which are on TOU tariff do not bid into the market. However, they react to the changing cost of electricity throughout the day, during times such as off-peak, mid-peak and on-peak periods. The other houses are part of the fixed and control groups. None of these houses bid into the market and their loads appear

as unresponsive on the demand curve.

A comparison of the simulated and experimental total load behavior is shown in Fig. 2.10.

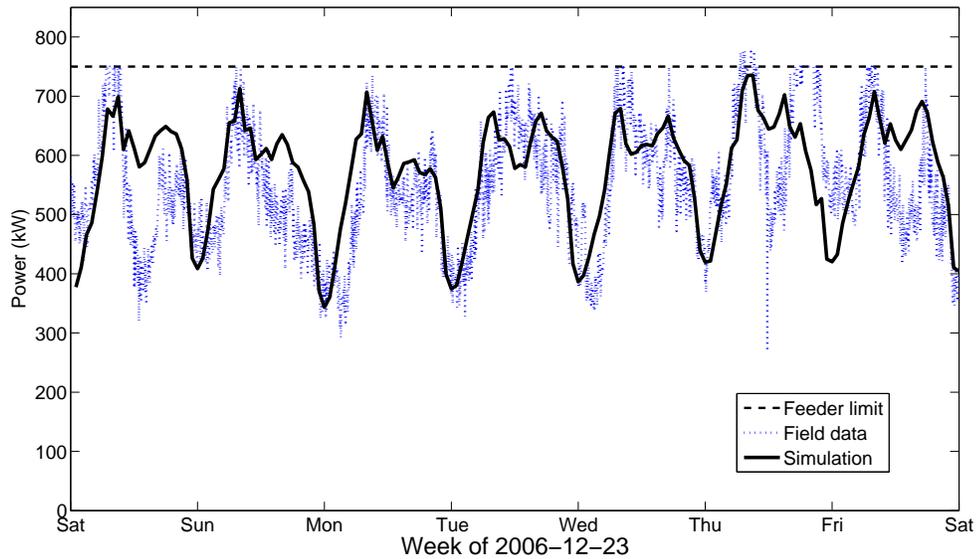


Figure 2.10: Comparison of simulation results with the demonstration project: Total load of all houses and commercial buildings over the week of the experiment

This includes all the price responsive and non-price responsive sellers and buyers. The salient features are well captured by the simulations, aside from the higher frequency fluctuations which are not resolved by the simulation time steps, and some discrepancies that are particularly noticeable at the end of the week (Fri.-Sat.). This is attributed to a systematic offset in solar gains in the model which used weather data obtained from a location (airport) that was cloudier. The model insolation levels are thus lower than the average insolation for the geographically distributed houses in the OPE. Overall, the results indicate that not only is the market behaving appropriately, but also provide additional confirmation that individual devices respond to the market behavior appropriately.

## 2.5 Summary

In this chapter a modeling and simulation framework is provided, in which an agent-based model is successfully used to validate a smart grid environment. In the following

chapter further investigation will be conducted to explore the effects of superimposing wind power on the previously validated model.

# Chapter 3

## Wind balancing

### 3.1 Introduction

Balancing demand and supply in power systems currently focuses mainly on the management of the supply side (supply side management) by controlling the supply in such a way that supply follows the demand (load following). However, variable electricity consumption combined with an increased penetration of wind power will make this an even more challenging task than it already is today. The ability to selectively switch loads off may be an effective way to offset the variability of wind and to meet demand during periods of insufficient generation. The potential and impacts of including responsive loads into the electrical power system with the presence of wind power will be the main focus of this chapter.

### 3.2 Electricity market behavior and proposed bidding mechanisms

An overview of a simplified overall smart grid electricity system model is shown in Fig. 3.1. It incorporates an electricity market, end-use models, generator and electric load models. Price signals are used to change the traditional behavior of loads in order to achieve market based demand response reaction.

The market model represents a double auction RTP electricity market with sellers and buyers bidding into a common market. The basic market interactions are illustrated in Fig. 3.2.

Appliances and other end-use devices in residential homes or commercial buildings

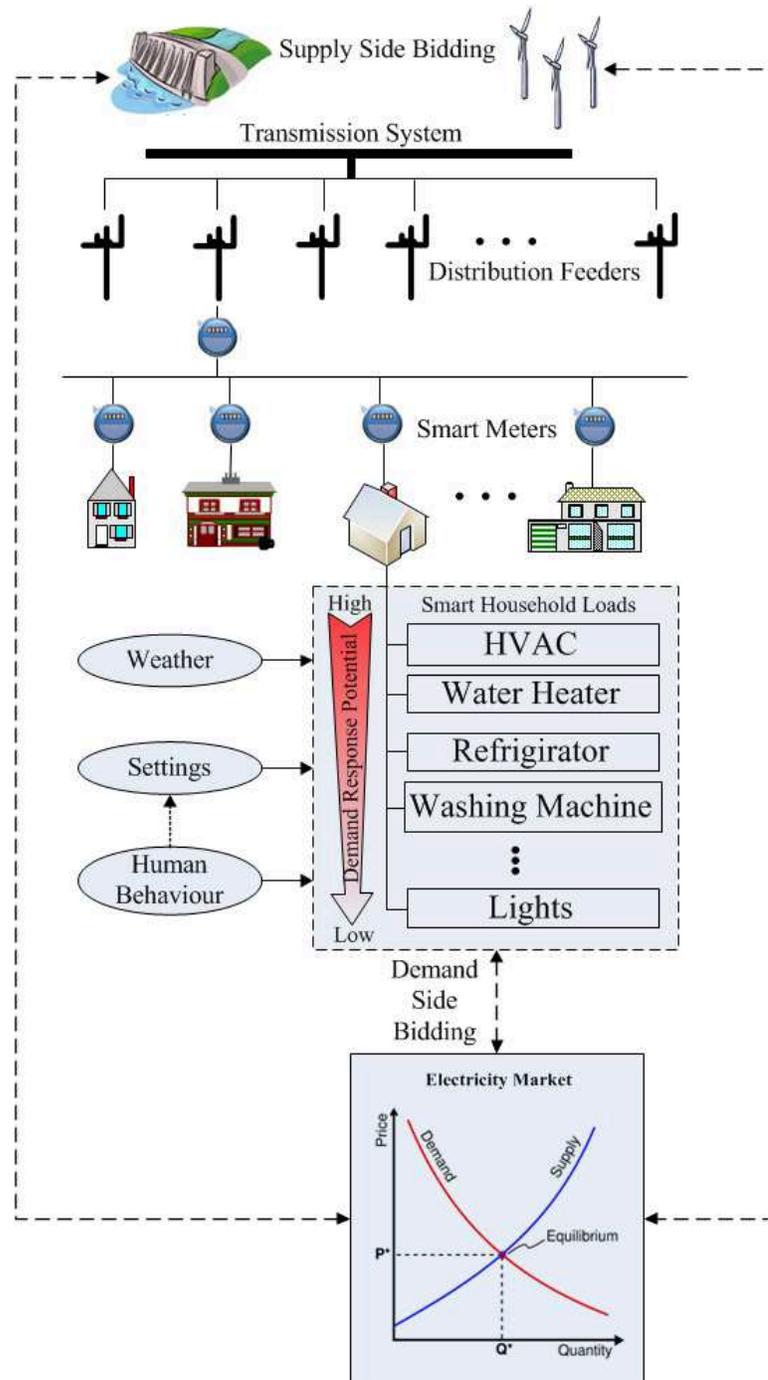


Figure 3.1: Smart grid system model

represent buyers. Appliances, such as HVAC systems and water heaters are equipped with intelligent controllers [19], which independently and automatically place price and power demand bids into the market. The electricity suppliers represent the sellers,

who also place price and power bids into the market. The intersection point of the supply and demand curves sets the market clearing price and quantity of power.

Fig. 3.2a illustrates how all parts of the loads and all suppliers contribute to setting market prices. Unresponsive loads, such as lights, bid the maximum price into the market in order to guarantee that they remain in operation. Although the bid price of the unresponsive loads is always fixed at the maximum bid price, the changing bid quantity will result in a shift of the demand curve and thus influence the clearing price. Responsive loads vary their bid prices according to their internal states and power needs. Generators that place bids below the market clearing price are guaranteed to sell power at that clearing price. Consumers who are on RTP and TOU contracts may respond to the changing market prices and curtail their demand when prices are high. Customers who are on fixed contract do not react to market prices and, along with other unresponsive loads, they form the unresponsive part in the demand curve.

Fig. 3.2b illustrates a new market event, in which the supply of wind power to the overall power mix is reduced. This results in a new and higher market clearing price. As a consequence, some buyers, whose bids were previously successful, are now below the higher clearing price and consequently have to shut off. This example illustrates how demand response operates, and how the desired demand behavior to changing wind power is achieved.

### **3.3 Wind power integration**

This section examines the impacts of demand response on wind power integration. First wind power is added to the previously validated model of the OPE. With the expected simulation behavior of the OPE being maintained the model was then scaled up to a larger model by introducing 35 MW of wind power and increasing the population to 10,000 houses. This larger model shares the model framework of the validated OPE model and provides a larger and diverse basis than the OPE for further study.

#### **3.3.1 Introducing wind power to The Olympic Peninsula Project**

Wind power was not part of the Olympic Peninsula Demonstration Project. The incorporated wind power output data shown in Fig. 3.3 were derived from 10-minute wind data sets measured at the William R. Fairchild International Airport (KCLM),

located within the Olympic Peninsula demonstration area. The wind speed was converted to the hub height of an Enercon E-33 wind turbine and the power output calculated using its power curve.

Wind power is an additional supply to the existing power generation mix, connecting in a way similar to the micro-turbine. This means the wind power is located downstream in the simulated feeder, adding to the overall power capacity of the feeder. It is modeled as a negative load, which bids its corresponding power capacity and price into the market. Wind power generators have no fuel cost and usually place low (zero) market bids into the market. This ensures that the bids are below the market clearing price and this guarantees that the electricity from wind power will be sold. However, as a consequence, a market situation, such as that shown in Fig. 3.4 (a) when a high wind power meets low demand, electricity will be sold for \$0/MWh.

The strategy of placing bids of \$0/MWh works until wind power penetration increases to the point where electricity generation from wind meets or exceeds the demand so often that a bid and market price of \$0/MWh becomes uneconomical. At this stage a new bidding strategy that includes the real production costs of wind power generation such as capital cost, maintenance cost and wind integration cost is required. As electricity demand and supply change with time, different market situations arise. For example, if electricity generation from wind power drops, generation from other, higher-priced, power sources will result in a higher market clearing price, such as shown in Fig. 3.4 (b). In response, loads with bids that are lower than the market clearing price will switch off. Thus loads are responsive to decreasing power generation from wind power.

### 3.3.2 Scaled up model

The previous modeling methodology is now applied to a RTP-only model with 10,000 residential houses and increased wind power bidding into a double auction electricity market. The supply side is represented by a 35 MW wind park consistently bidding at \$0/kWh and hydro supply always bidding at \$0.1/kWh. Fig. 3.5 shows how a single residential house responds to varying wind power.

The responsive demand is represented by an HVAC load that bids into the market. When wind power decreases, the clearing price rises and the load bid falls below the clearing price. Accordingly, the HVAC system loses the bid and switches off.

Such an event can be observed in Fig. 3.5 at around 5:30AM, where a drop in wind power causes the heating system to switch off for approximately one hour. As a consequence, the air temperature of the house drops and eventually approaches the lower temperature limit (17°C for example). The HVAC system now reenters the market with a bid of the maximum possible market price (the preset cap-price) to prevent the temperature from dropping below the minimum set value. The formerly responsive HVAC load is now unresponsive and cannot react to market signals as it is maintaining the preset minimum temperature. This leads to a high variability of the bids, however the thermostat automatically protects against fast cycling of the device.

As wind power increases the clearing price falls and the HVAC system recovers and its bids remain below the market price cap. However, high wind power regimes can also result in unresponsive load behavior, because wind drives the price down and HVAC bids are always successful. This will result in indoor house temperatures close to the upper temperature limit. At this stage, the HVAC system stops purchasing power and no longer participates in the market.

### **3.4 Summary**

Simulation results show that traditionally passive loads may become a resource that can mitigate the consequences of wind's variability. Various residential loads that are the preferred candidates for demand response strategies have been identified. Changing the behavior of these loads depending on wind power deficits or wind power surplus is a fundamental issue of this research work. The impact of demand response on generator cycling and the consequences on the mitigation of green house gas emission will be evaluated in subsequent chapters.

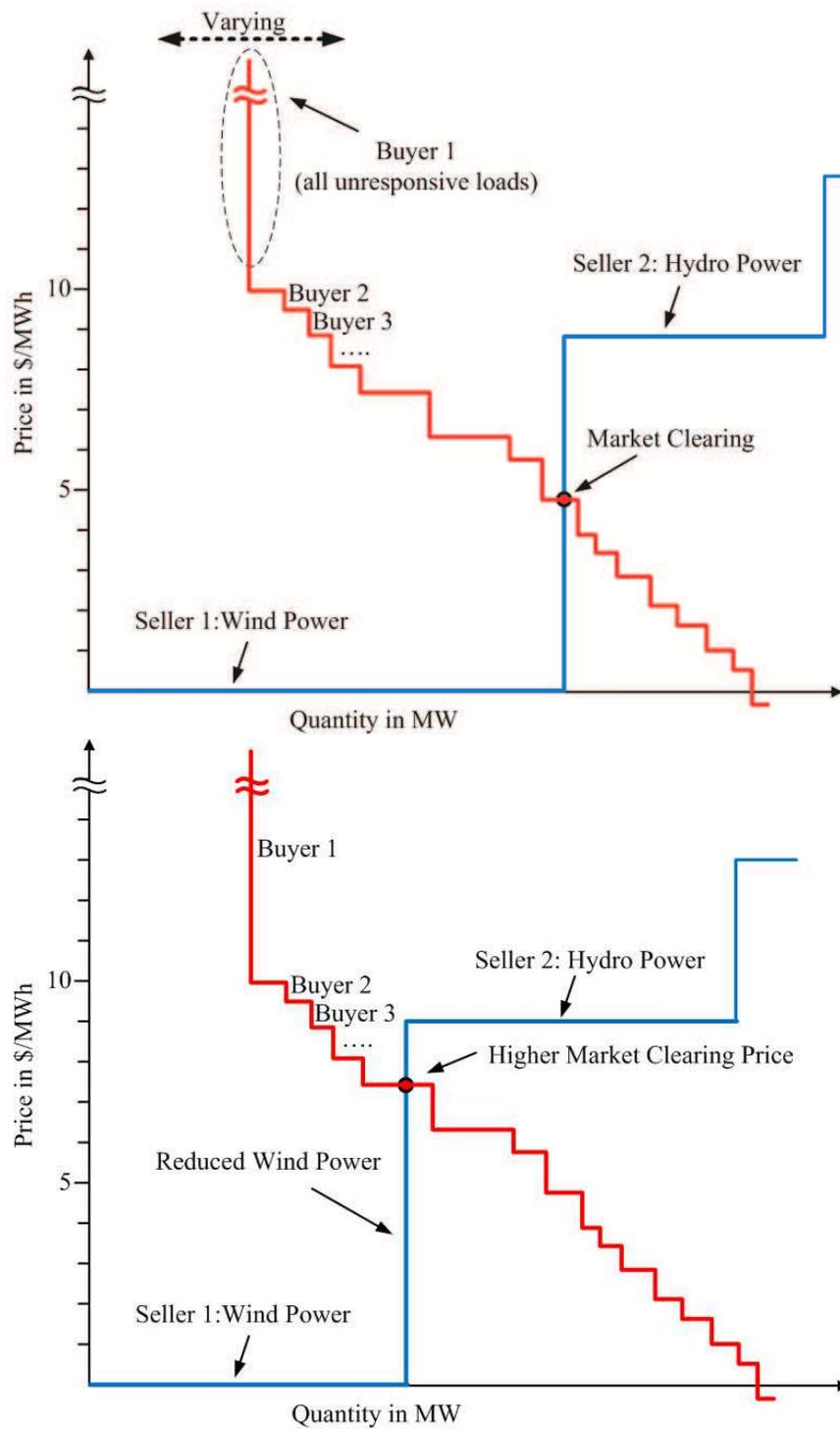


Figure 3.2: The principle of a double auction real-time (RTP) electricity market:  
 (a) Market event N: suppliers (wind and hydro) and demanders bid into the market and determine the market clearing price  
 (b) Market event N+1: a decline in wind power leads to a higher market clearing price and the loads automatically switch off

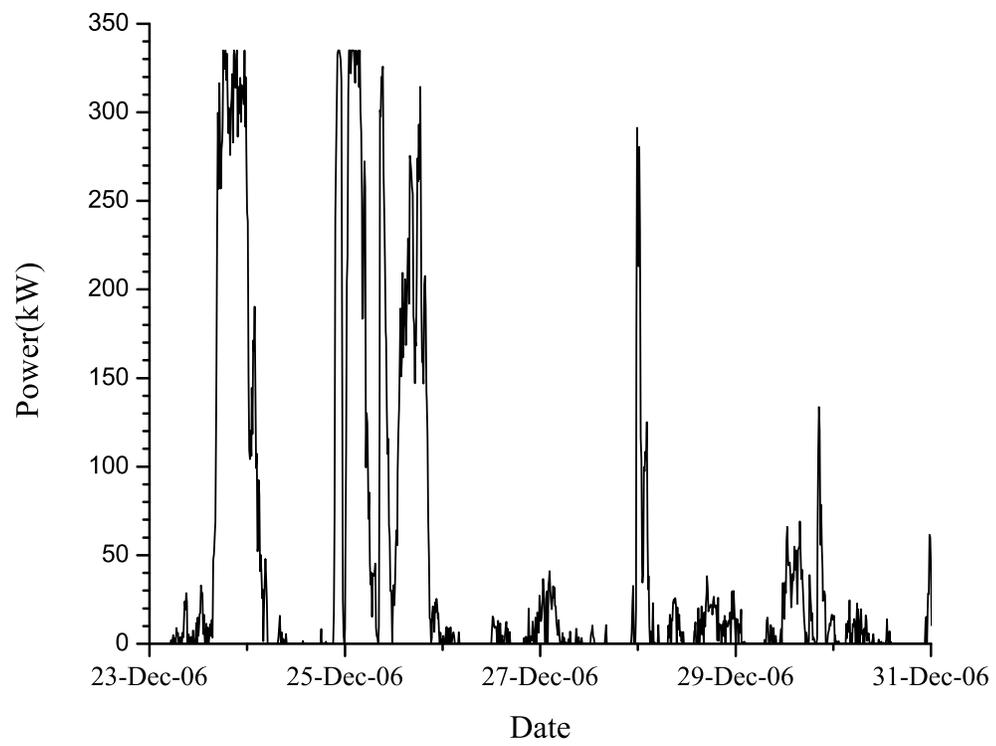


Figure 3.3: Simulated wind power data for the week of the experiment

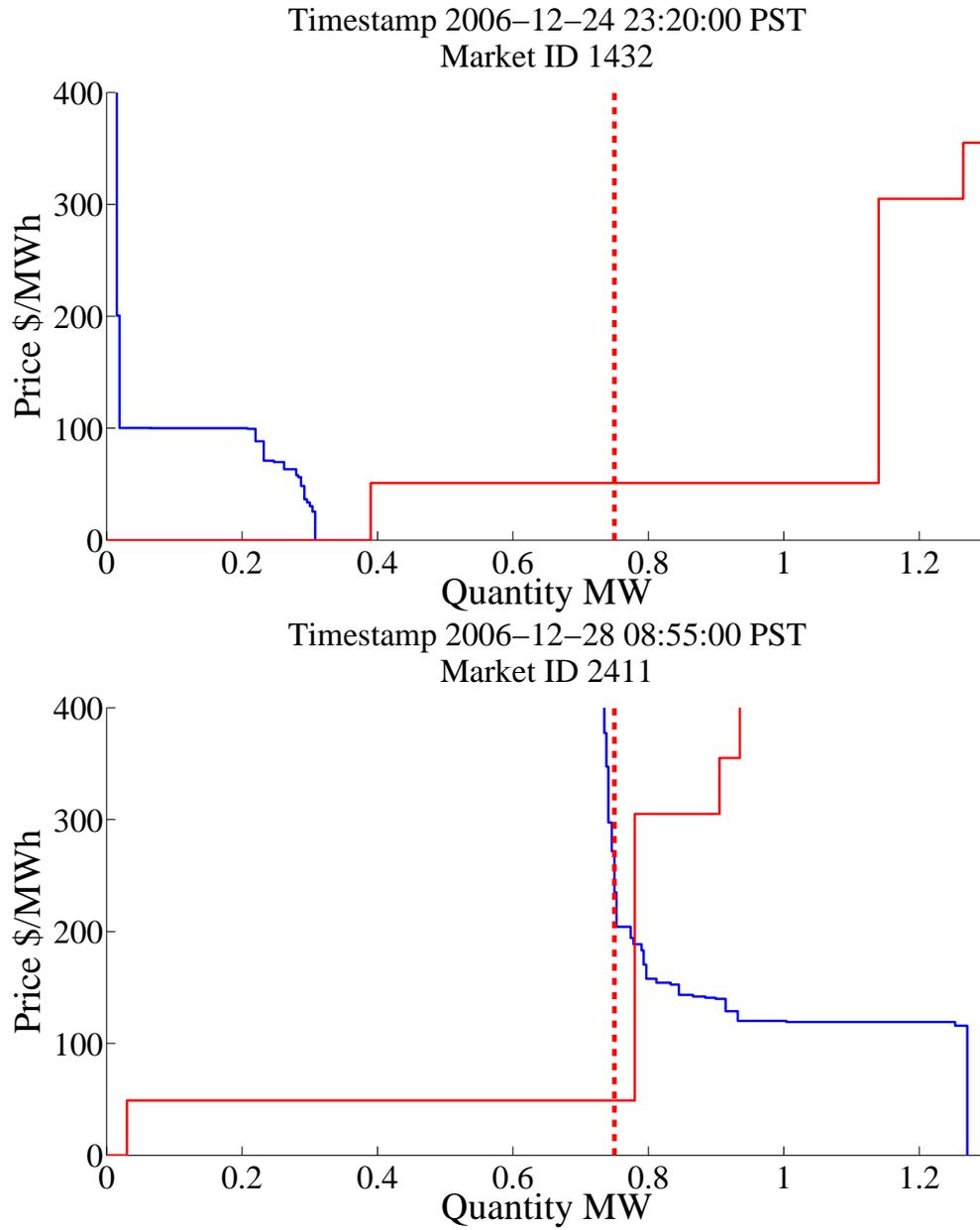


Figure 3.4: Simulation results of superimposing wind power on the validated model, showing two different scenarios:

- (a) High wind power and low demand
- (b) Low wind power and high demand

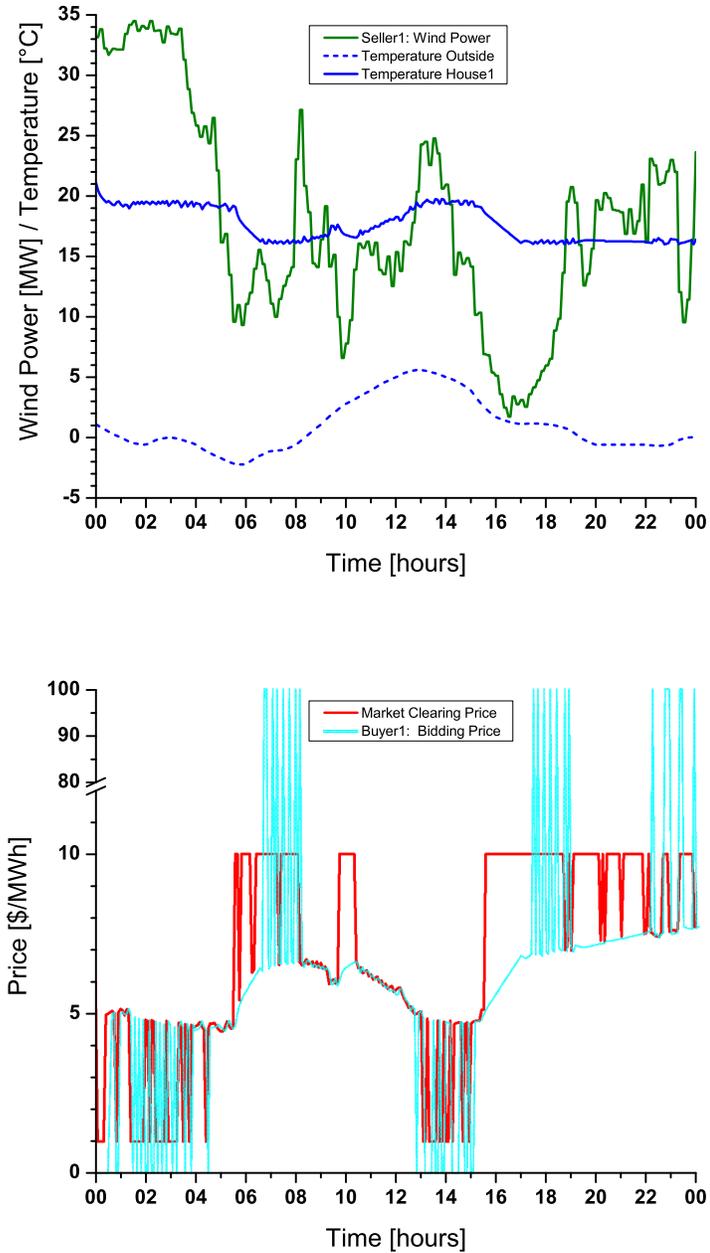


Figure 3.5: The behavior of a single house over a 24 hour period to varying wind power:

(a) Indoor house temperature following wind power

(b) Varying wind power leads to a varying market clearing price and the switch off of loads

# Chapter 4

## Mitigation of greenhouse gas emissions

### 4.1 Introduction

Energy use and climate change are closely related. In industrial countries, electricity consumption can be subdivided into commercial, industrial and residential electricity demand in almost equal parts [12]. Fossil fuel based electricity generation still has a dominant share of overall electricity generation and is a major factor in the contribution to GHG emissions.

The replacement of fossil fuels by renewable energy sources is viewed as one of the most viable options for large scale mitigation of greenhouse gas emissions. However, our current electricity system was not designed to cope with the large scale integration of variable, renewable energy resources, such as wind and solar. A more flexible power system is required [30] that also includes the demand side within an integrated system approach.

This chapter investigates the energy usage of residential homes and their contribution to GHG emissions, and explores how both demand response and the additional use of wind power can mitigate emissions of GHG. These emissions depend on the generation mix (primary energy) that is used to generate the electricity.

A detailed smart grid power system model is created, where suppliers and demanders are bidding into a double auction electricity market. In this scenario, the demand is represented by 1,000 residential houses and the supply by a hypothetical highly fossil fuel-based generation mix. Wind power is superimposed as an additional

supply source. Based on this model the following questions are explored:

- What is the demand curve of these houses?
- How much GHG will be emitted based on the assumed generation mix?
- What happens when DR is introduced to the system and how does this affect GHG emissions?
- What happens when wind power is introduced into the initial system (without DR) and how does this affect GHG emissions?
- How does the combination of both DR and wind power affect GHG emissions?

## 4.2 System model and simulation approach

The system model contains all the traditional components of an electrical power system. This includes the transmission system, which is modeled as a single slack bus, and a detailed representation of a distribution system. The supply consists of different generators such as hydro, coal, nuclear and natural gas. All supply options have different generation costs and different GHG emissions associated with them. The demand side consists of 1,000 residential houses with a diversity typical of houses in the Pacific Northwest. Additionally, a RTP electricity market is introduced where not only the supply side, but also the demand side places bids into the market.

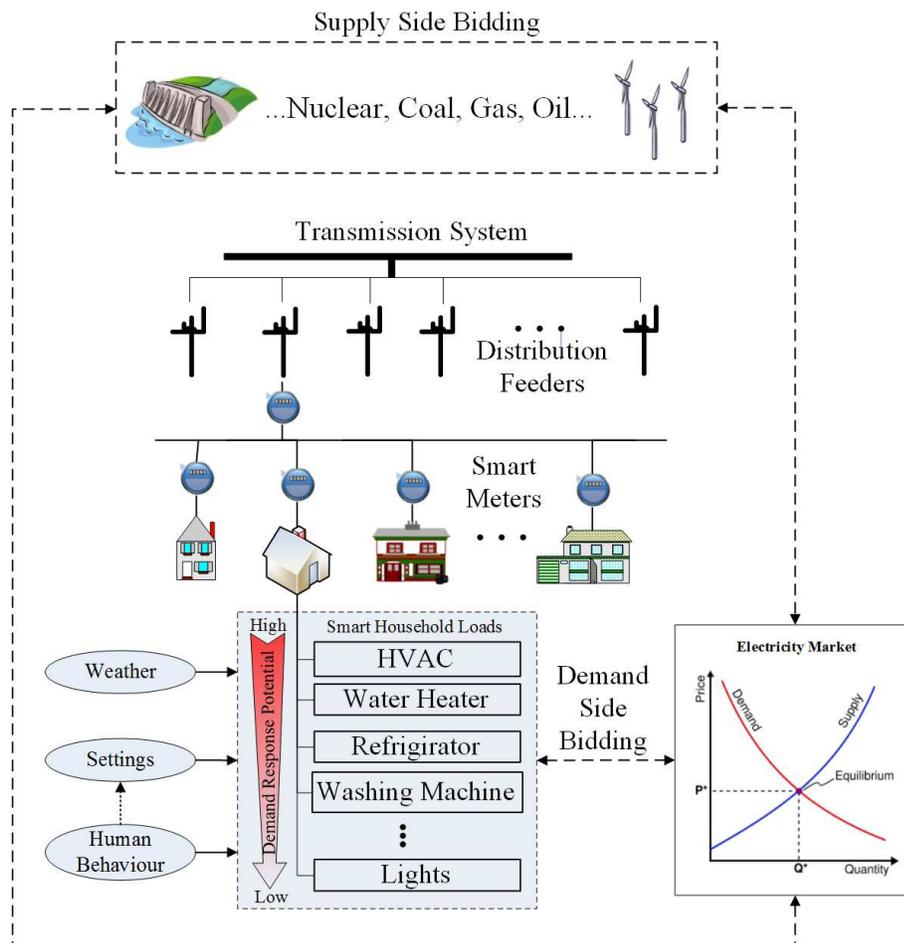


Figure 4.1: System model

The following sections give further background about the components of the sys-

tem model. This includes the modeling approach for achieving a diversity of loads, the supply side in the overall system model, and the methodology of GHG emission tracking .

### 4.2.1 Demand and load modeling

The demand side consists of 1,000 residential houses with various appliances as shown in Fig. 4.1. This demand is strongly influenced by factors such as weather, thermostat settings, and other human behavior. Generally, loads can be subdivided into two types: responsive and unresponsive loads where some loads are more suitable for demand response than others.

#### Load diversity

To achieve effective demand response interactions, a diversity of loads is important to ensure that the household loads do not all react in the same way. This is achieved by creating model houses, each with different loads, load properties, and load behavior. Load behavior varies due to factors, such as house size and design, energy efficiency, occupancy, and load usage.

Fig. 4.2 illustrates the load behavior of two houses with quite different properties. The figure shows the operation of the heating system with a conventional thermostat and the influence of insulation on the heating system power consumption of the two houses.

The heating system contributes greatly to the overall power consumption of an individual house. Additionally, the different setpoints of thermostats will have an impact on the overall power consumption of each house. The distribution of heating setpoints of all the residential homes is shown in Fig. 4.3 and illustrates a diversity of set points with all having the same thermostat bandwidth of 2°C.

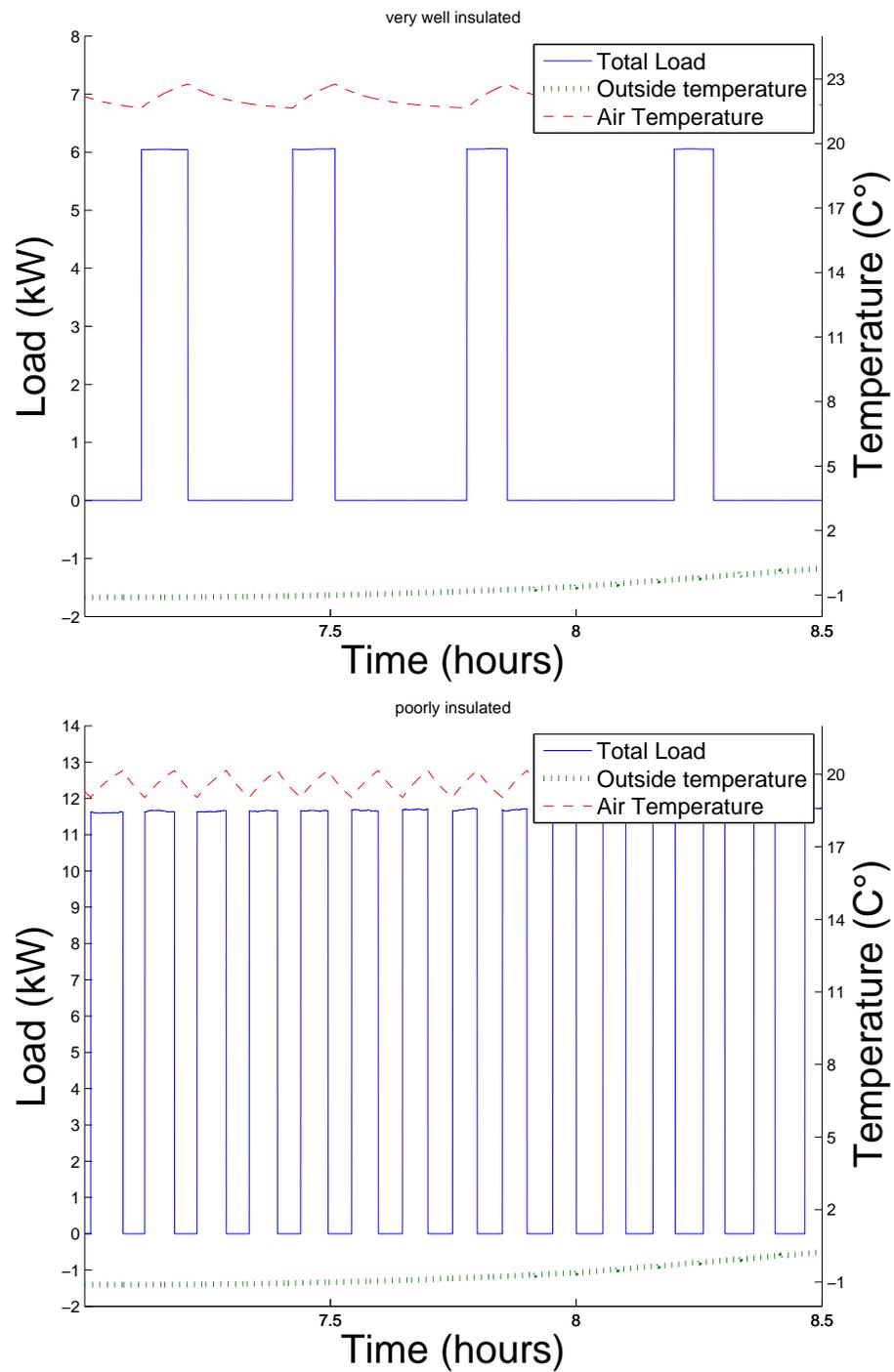


Figure 4.2: Comparison of the load behavior of the heating system in two distinctly different residential houses:

- (a) Good insulation
- (b) Poor insulation

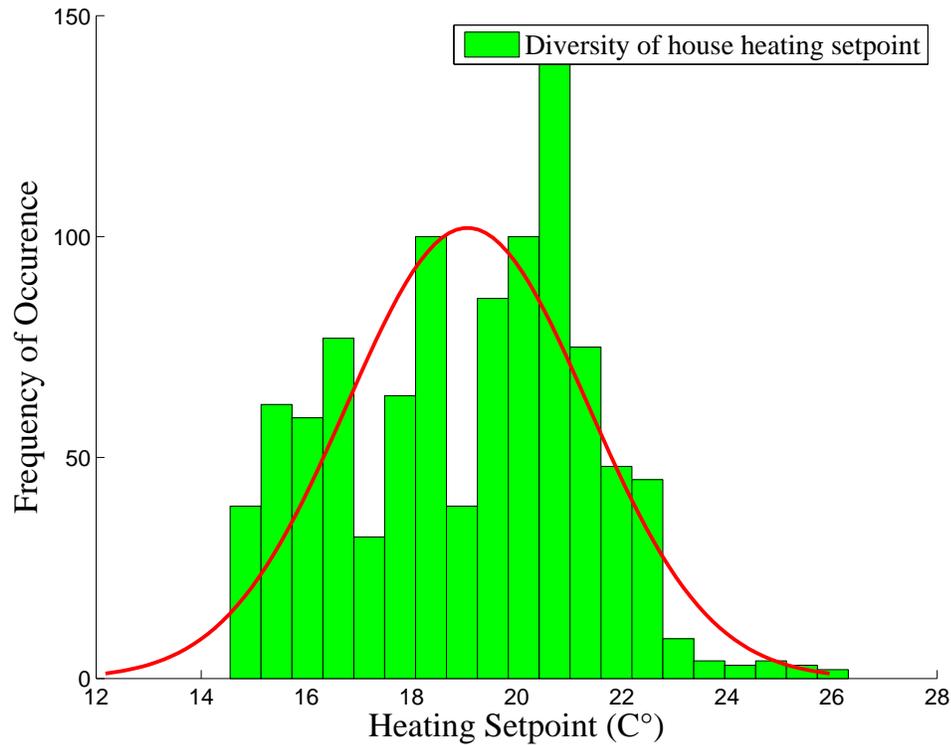


Figure 4.3: Distribution of heating setpoints for all 1,000 modeled residential houses

### Unresponsive loads

Unresponsive loads do not change their normal operational behavior. These loads do not react to externally-induced signals that may be derived from, for example, market prices, grid frequency or voltage deviations.

An example of a load curve with unresponsive demand behavior is shown in Fig. 4.4. It represents the aggregated demand of 1,000 modeled residential homes each with its typical appliances and heating system as the major load. This type of residential load curve is typical for residential consumers during a Pacific Northwest winter. Although the demand will change due to human behavior, thermostat settings and weather, the load curve represents a relatively fixed and predictable demand. The demand does not respond to changing situations in the power system, such as power deficits or surplus. The loads show a passive behavior.

### Responsive loads

Responsive loads have the ability to react to price or other signals from the grid; they can respond by increasing or decreasing their power consumption. Preferably, this

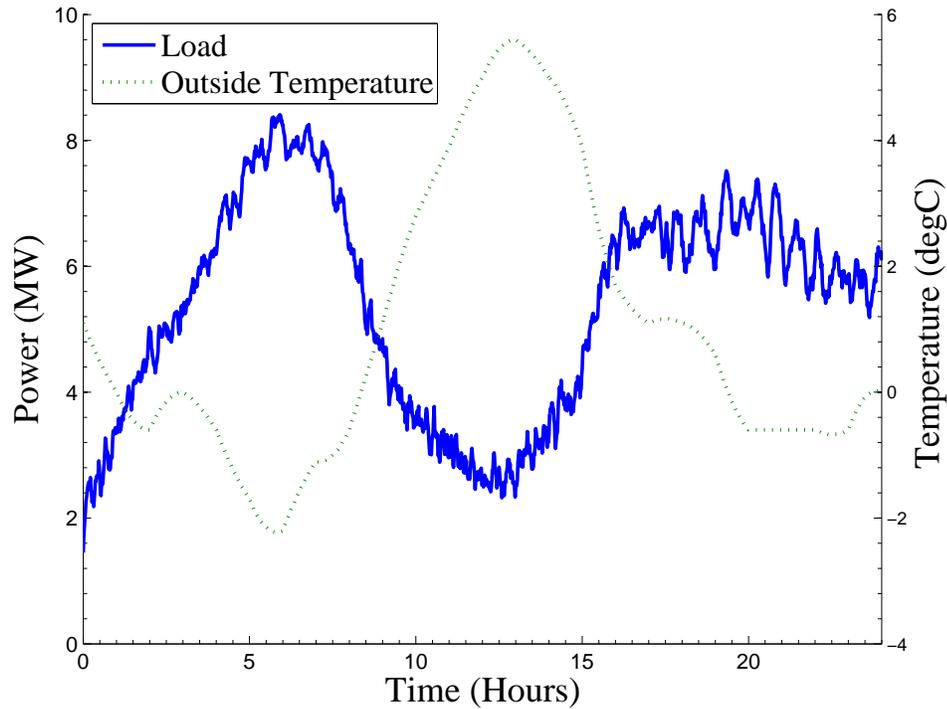


Figure 4.4: Aggregated demand curve of 1,000 typical residential homes in the Pacific Northwest during a winter season

should be done without reducing either customer comfort or control. Loads with an intrinsic storage capability are the preferred candidates to interrupt service without affecting user comfort too much.

To make some residential loads responsive, the heating system in every individual house is equipped with a controller. This controller adjusts the thermostat base setpoint depending on the price signals received from the electricity market and on the current room temperature. High market prices usually result in lower heating setpoints and low market prices in higher heating setpoints and, as a consequence, varying price bids as shown earlier in Fig. 2.3.

The base setpoints of the "transactive controllers" are identical to those in houses equipped only with conventional thermostats. However, to ensure each house equipped with a transactive controller responds accurately to the electricity market, the thermostat deadband is set to zero. The upper and lower limits of the range from which the base heating setpoint is allowed to vary are thus set by the transactive controller. Both the base set point and the range limits can be chosen by the consumer. The diversity of range settings in the 1000 houses of the system model are shown in Fig. 4.5.

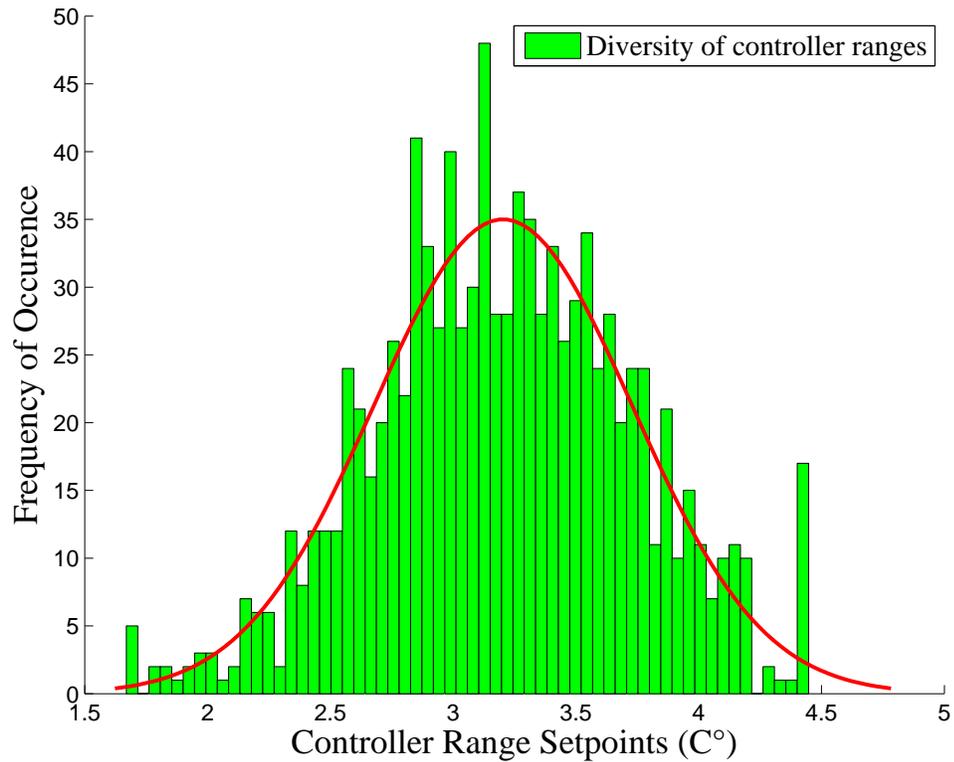


Figure 4.5: Diversity of controller ranges ( $T_{\max}-T_{\min}$ ) of 1,000 individual houses

An initially responsive load (such as a heating system) can become unresponsive when the maximum limit of variability is reached. This can occur in the case of "longer periods" of power deficit or power surplus, which consequently may result in maximum or minimum and static bid prices until the situation changes and the load recovers.

### 4.2.2 Supply side modeling

The supply side is represented by a hypothetical generation mix consisting of hydro, nuclear, coal, gas and oil- based power generation facilities as shown in Fig. 4.6.

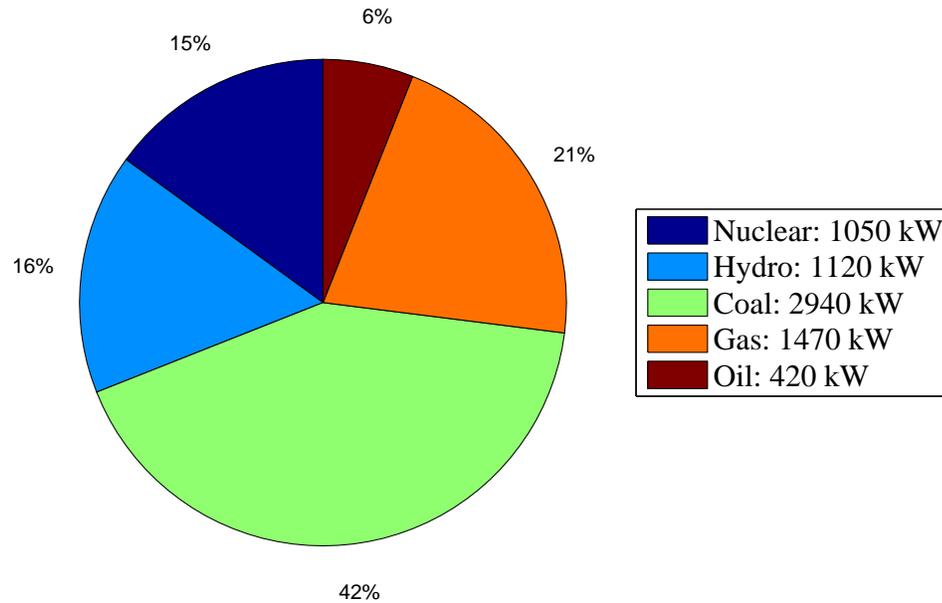


Figure 4.6: Available capacity of a global generation mix

Each of these generators has different electricity generation costs, that take into account the generator cost curve, startup cost, minimum runtime and early shutdown cost. A breakdown for the individual generator cost and runtime constraints is given in Table 4.1.

Table 4.1: Assumed operations and maintenance cost, startup cost, early shutdown cost and minimum runtime per generator (power plant)

	O&M (\$)	Start-up (\$/MW)	Shut-down (\$/MW)	minimum runtime (min.)
Nuclear	8	55	55	360
Hydro	15	15	15	5
Coal	40	55	55	240
Gas(CT)	95	25	25	30
Oil(CT)	245	40	40	30

The values are assumptions and based on information from various reports and

websites. The cost to produce electricity varies widely, where hydro and nuclear generators have typical running costs below \$10/MWh, while the generation costs for a combustion turbine can be in the range of \$100/MWh or more.

The supply bid price curve is obtained by combining the costs of all the individual generators (excluding wind) and results in a generation stack composition as shown in Fig. 4.7. Together with an assumed unresponsive demand (the vertical line) the clearing price is determined. Each of the vertical lines represent a certain demand scenario, where the off peak demand results in a low market clearing price and the peak demand results in a high market clearing price. Also illustrated is a scenario of extreme demand that could result in insufficient supply and the market would not clear. This specific event would cause a power outage.

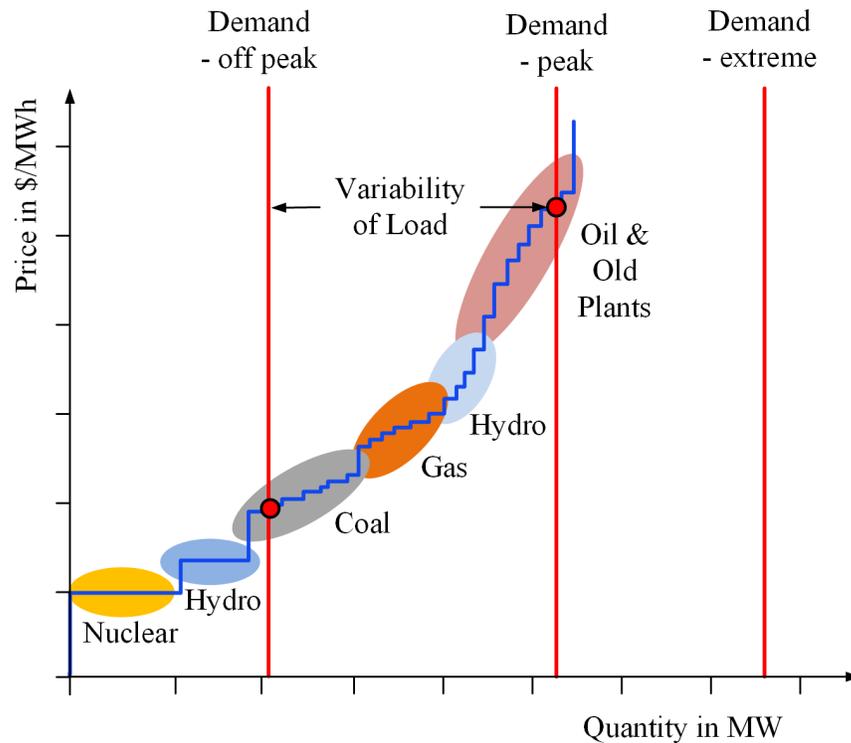


Figure 4.7: Various suppliers are bidding into the market with loads as price takers (unresponsive demand)

The effect of adding wind power into the generation mix can be seen in Fig. 4.8. Wind power always bids with the lowest price of \$0/MWh. As a consequence, as the amount of wind power increases, the supply bid curve is shifted further to the right. Higher cost generators may lose the bid and be forced to switch off or reduce power output.

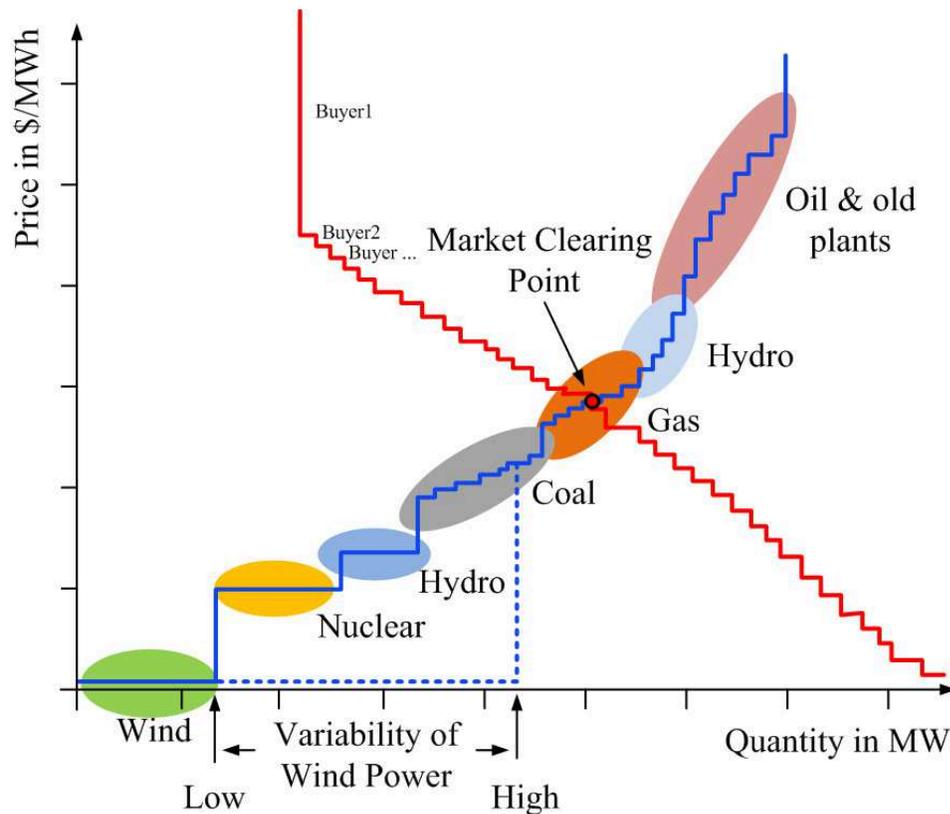


Figure 4.8: Different suppliers and demanders are part of a double auction real-time electricity market

The wind power data are based on a wind integration study conducted by BC Hydro [11] and represent data from a potential 30 MW wind park. These data had a resolution of 10 minutes and were processed into 5 minute resolution via linear interpolation and scaled down to maximum power output (installed capacity) of 1.8 MW. The applied wind power data for a seven day period, the first week in January 2009, can be seen in Fig. 4.9.

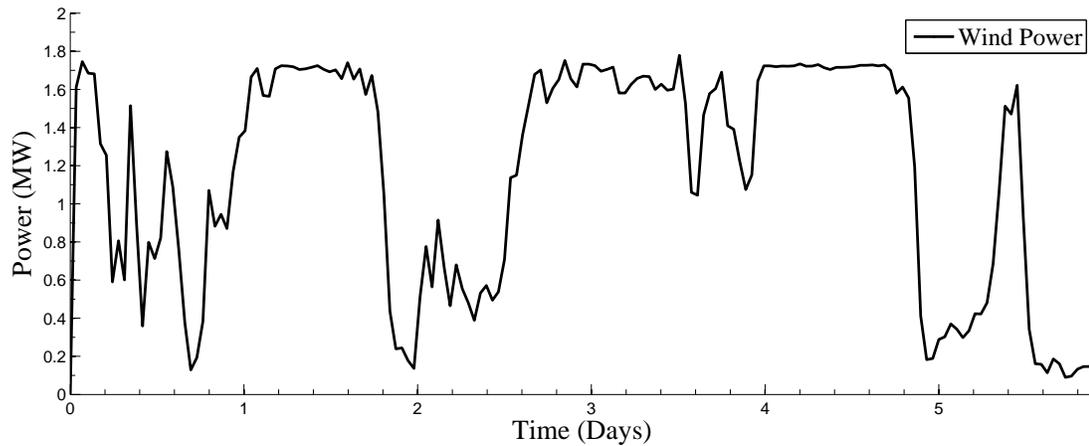


Figure 4.9: Wind power during the first week of January

### 4.2.3 Greenhouse gas emission tracking

The supply side in the model system is based both on low GHG emission generation facilities and on fossil fuel- based electricity generation. The model is confined to assessing operational GHG emissions. GHG emissions based on life cycle assessment [43] are not considered. Hence it is assumed that the GHG emission from hydro, nuclear and wind power generation can be neglected. GHG emissions for coal, gas and oil-based generation facilities are calculated in the methodology shown in Fig. 4.10. The methodology considers decreasing efficiency of the generators by lower utilization, that may be caused by demand response effects and renewable energy supply.

Table 4.2 shows the generation heat rates at different capacity factors for three different fossil fuels: coal, gas and oil. Coal has the highest efficiency, gas has the lowest efficiency and oil is between the two. The efficiency of all three fossil fuel generators increases with decreasing capacity factor (CF).

Table 4.3 compares the emissions from natural gas, oil and coal-fired generation facilities. Coal is usually used as a base load power plant and gas is usually used to satisfy fast power changes within the electricity system. These changes are caused by fast changing demand and other contingencies within the transmission, distribution and supply system. Currently, oil is still used to satisfy peak demand. However, gas and hydro facilities can also function as peaking power plants and, where available, have replaced oil. Gas plants have the lowest emissions, coal producing more, oil having the highest emissions.

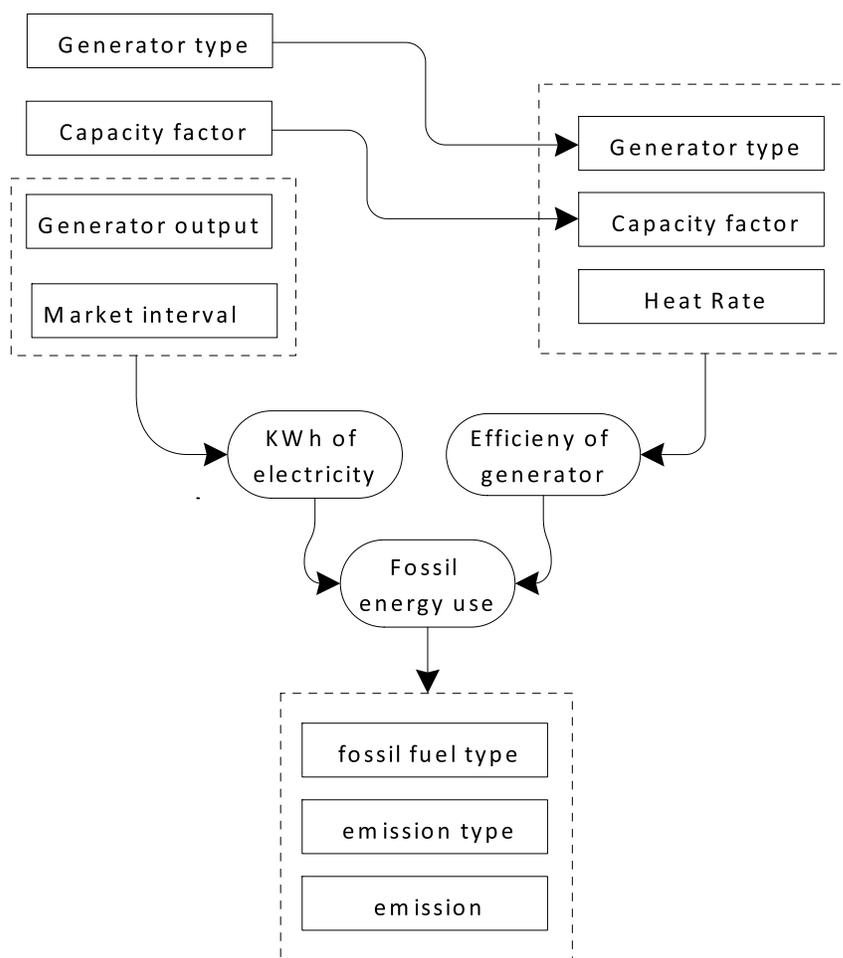


Figure 4.10: Methodology for GHG emission tracking, taking into consideration the capacity factors and efficiency for all individual generators and fuel types

Table 4.2: Typical fossil generation unit heat rates:(source: [3])

Capacity factor	Heat Rate in Btu/kWh		
	Coal	Gas	Oil
100% Output	8750	9200	9100
80% Output	8803	9255	9155
60% Output	9048	9513	9409
40% Output	9625	10120	10120

Table 4.3: Fossil fuel emissions for coal, gas and oil:  
(pounds per billion BTU of energy input)

Emissions in lb/MBtu	Coal	Gas	Oil(Petroleum)
CO2	205.573	117.08	225.13
SO2	0.1	0.001	0.1
NOX	0.06	0.0075	0.04

#### 4.2.4 Grid modeling

A modified IEEE4 feeder is used to model and simulate the distribution system. Although more complex distribution configurations can be found around the world, this simplified representation was chosen to accelerate the processing time of the simulation. Detailed feeder evaluations such as voltage, frequency variations and feeder overload are beyond the scope of this research and are therefore not included.

The modifications made to the IEEE feeder configurations shown in Fig. 4.11 include increased transformer and line ratings. Additional various bidding generators are added at bus1. Furthermore, another component (known as a capacity reference object) is attached at the regulator, and bids all the unresponsive loads into a double auction electricity market. 1,000 residential houses are attached at the low voltage side, and evenly distributed over the three phases.

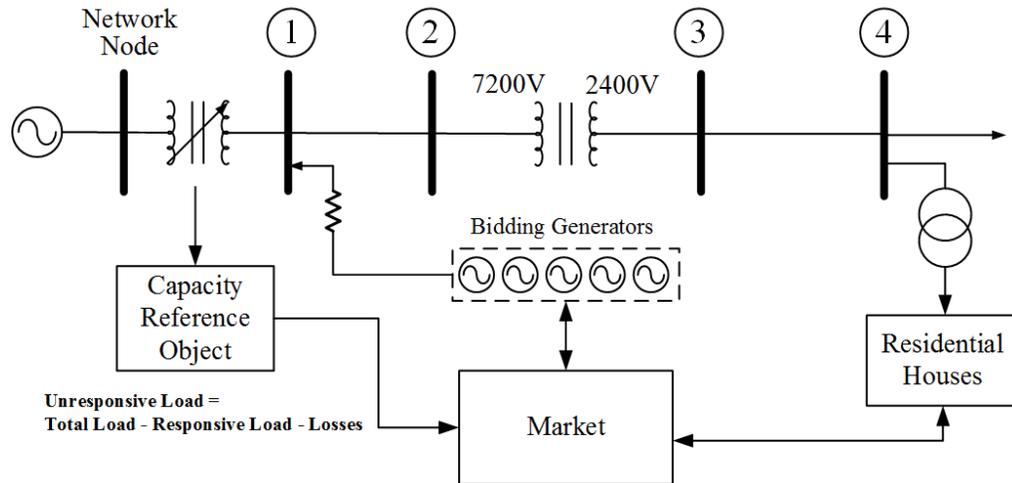


Figure 4.11: Modified "IEEE4 feeder" with 1,000 residential houses and five generators, unresponsive loads, all bidding into a double auction electricity market

### 4.3 Simulation results

All simulations cover the same seven day period during the first week of January 2009. A minimum timestep of 60 seconds and a market interval of 5 minutes were chosen. GHG emissions were monitored and accumulated for each generator every 5 minutes (i.e. each market cycle). Various simulations were conducted to investigate the following cases:

1. The base case scenario is an electricity system without either wind power or demand response.
2. The base scenario to which only wind power has been added.
3. The base case scenario to which only demand response has been added.
4. The base case scenario to which both wind power and demand response have been added.

It is expected that the effects of demand response on electricity use will reduce dependency on fossil fuel-based electricity generation. However, the anticipated mitigation of GHG emissions is dependent on the number and efficiency of those fossil fuel generators and especially on the capacity factor at which they will operate. Therefore, if a generator (the marginal seller) is forced to use less efficient fossil fuel power generation schemes this may lead to higher GHG emissions.

### 4.3.1 Base case

In this base case scenario the aggregated load of all residential houses bids into a double auction electricity market. In terms of market interaction all houses are price takers that accept any electricity price. This is illustrated in Fig. 4.12 by the vertical demand line that represents a bid into the market at the maximum market price (cap price). The vertical demand line changes with each market interval as the market progresses. This is represented by the horizontal double arrow line.

Various electricity generation facilities are present in the system. Fig. 4.12 shows competing fossil fuel-based suppliers bidding into the market. In this scenario there are no renewables in the generation mix. All the loads are unresponsive and so do not react to price signals from the electricity market. This mimics today's retail electricity market, where the demand is inflexible and consumers usually pay a flat rate for electricity.

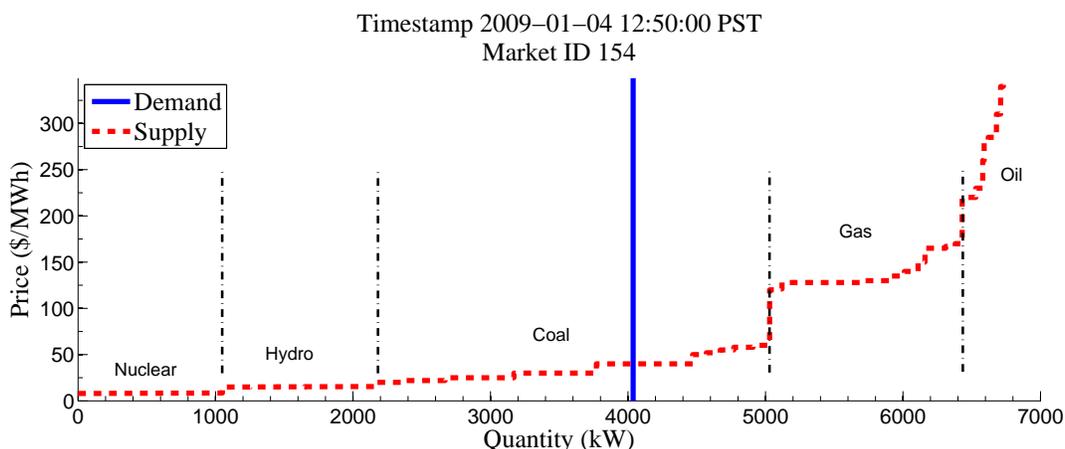


Figure 4.12: Various suppliers and the aggregated demand of all 1,000 houses are bidding into the market, where the demanders are price takers

A time-step simulation results for all market events over a period of one day are illustrated in Fig. 4.13 and compares the load curve and the market clearing quantity. As the market clears this will result in suppliers and demanders switching on or off, i.e. reacting to the changing market price. Ideally these two curve should line up, as the load should follow the cleared market quantity.

However, due to marginal buyer issues and an estimation of system losses there may be a mismatch between the curves as shown in Fig. 4.14 resulting in an error of up 6% for an individual market interval.

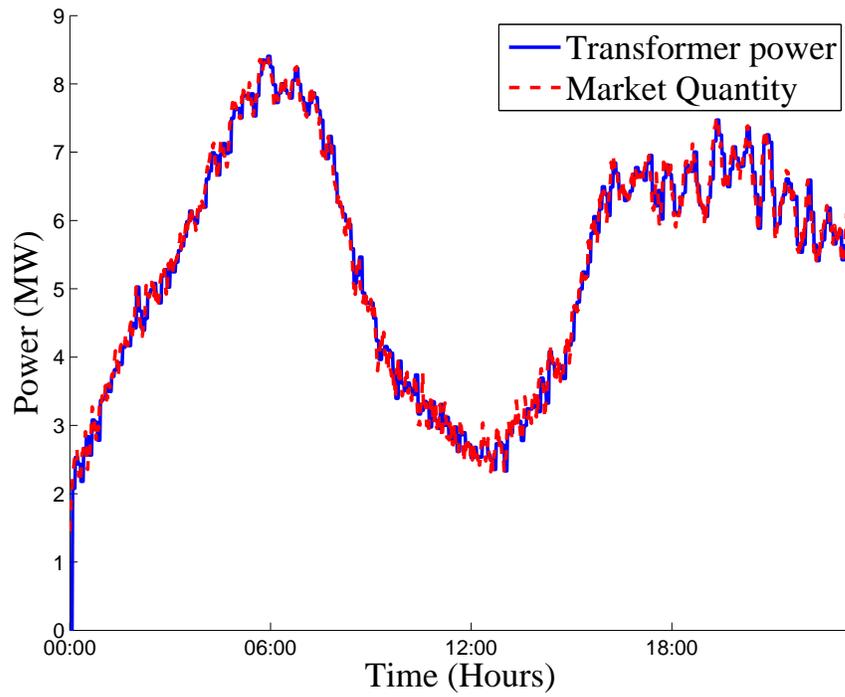


Figure 4.13: Real power vs cleared market quantity

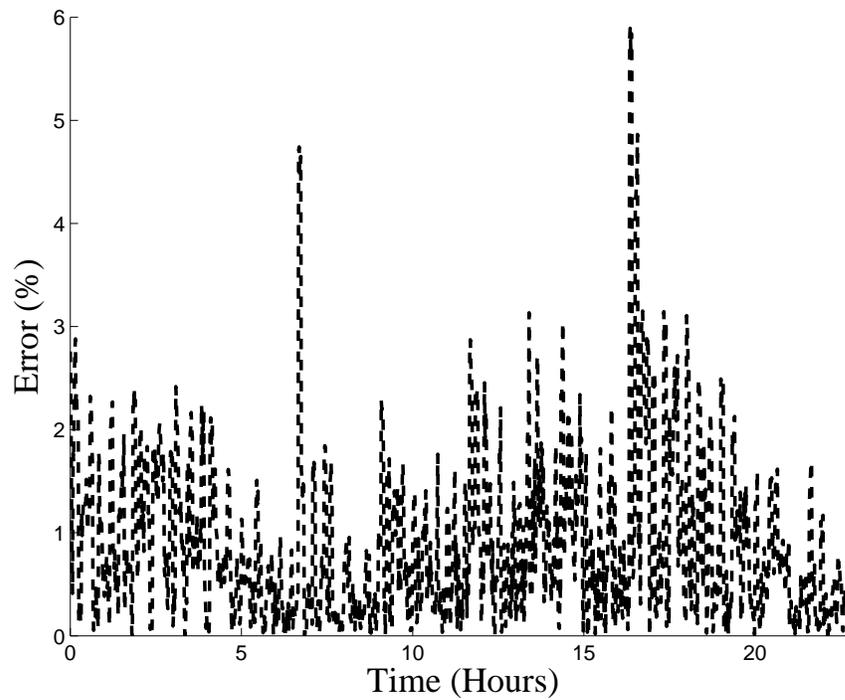


Figure 4.14: Error between cleared market quantity and actual load per market interval

A presentation of the accumulated power and market clearing quantity over time is shown in Fig. 4.15 and indicates that the error can be neglected from the energy perspective.

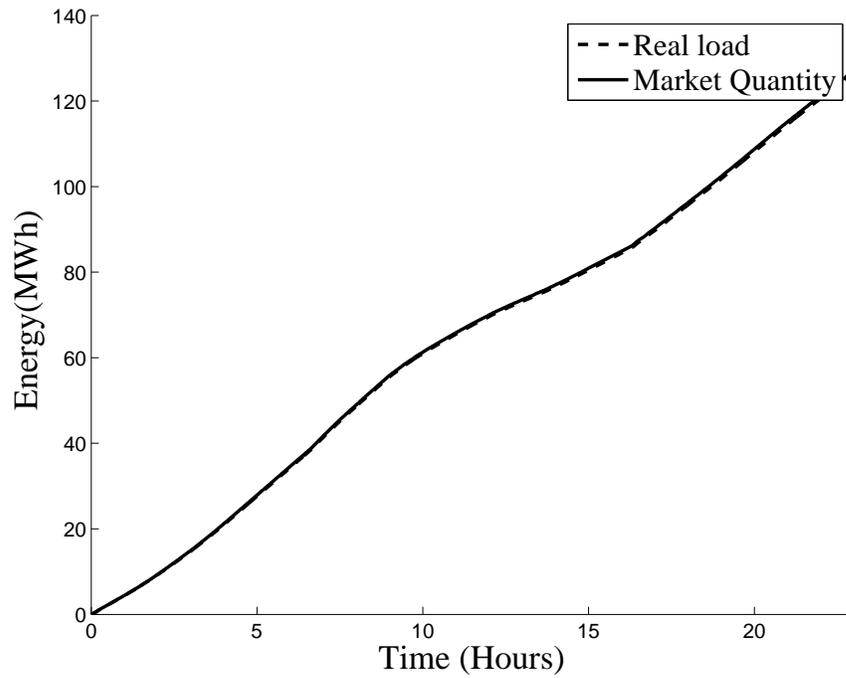


Figure 4.15: Accumulated power and market clearing quantity over time (energy)

### 4.3.2 Base case and wind power

In the second scenario wind power is added to the generation mix, introducing more variability to the power system and resulting in a change of the net load.

Depending on the amount of wind power, conventional generation will be fully or partly displaced and the generators are forced to switch on and off more frequently. The impact of wind power on the generation stack in a high wind event is shown in Fig. 4.16

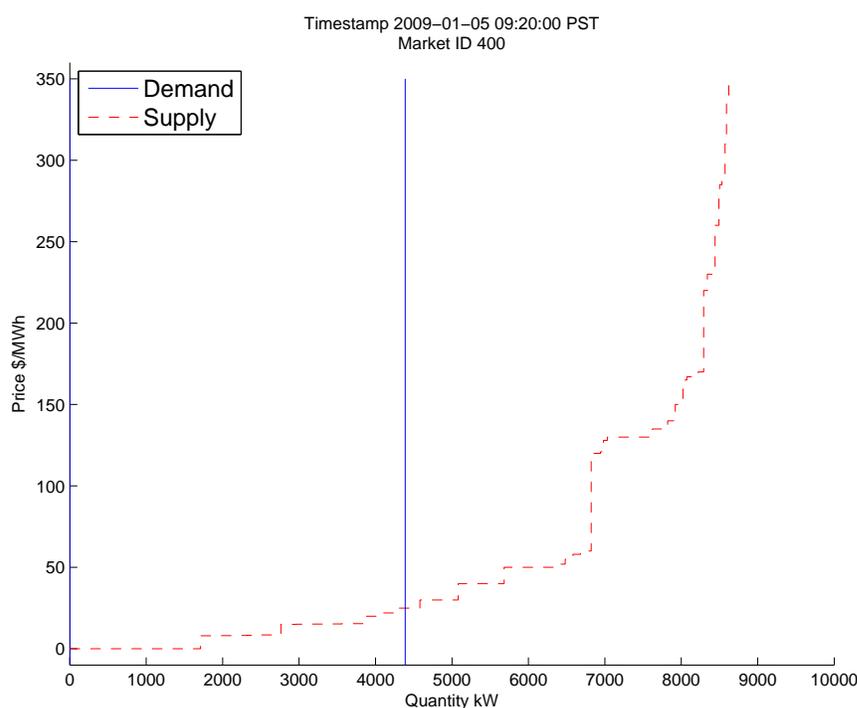


Figure 4.16: Market interaction with wind power and the aggregated load of all individual houses bidding into the market during a high wind power regime

### 4.3.3 Base case and demand response

In the third scenario demand response is added to the base case system, to allow the heating systems of all 1,000 residential houses bid into the electricity market and react to electricity prices. Fig. 4.17 illustrates an average load event leading to relatively average electricity prices. The graph also shows a variety of bid prices indicating a sufficient diversity of houses with different characteristics. The fraction of unresponsive loads is relatively small, showing that the thermal storage capacity is not

exploited and the bidding behavior is still adequate.

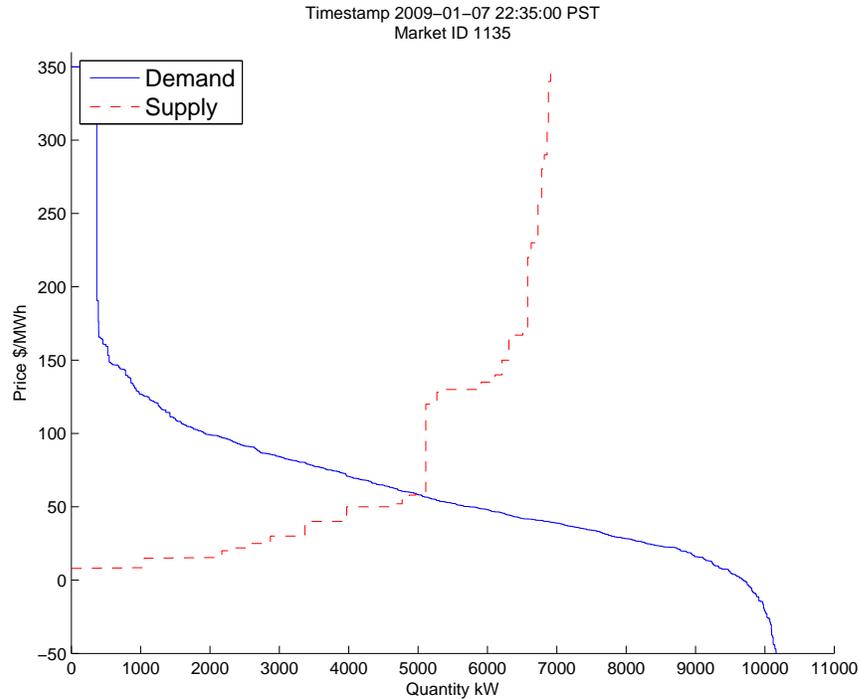


Figure 4.17: Market interaction with a generation mix without wind power and all individual residential houses bidding into the market

#### 4.3.4 Base case, wind power and demand response

In this final scenario wind power and demand response are added to the system. Depending on the amount of wind power "conventional generation" such as coal is displaced and this leads to lower market clearing prices. Additionally loads respond to changing market prices.

In Fig. 4.18 a high wind power event can be observed. The coal power is switched off and also hydro power has been partly displaced. The vertical line represents the non-demand response case, where the clearing quantity is even lower.

Fig. 4.19 compares the load curve with and without demand response. It shows that demand response clips the top from the load peak and fills in the valleys at low demand and lower electricity prices (rebound effect).

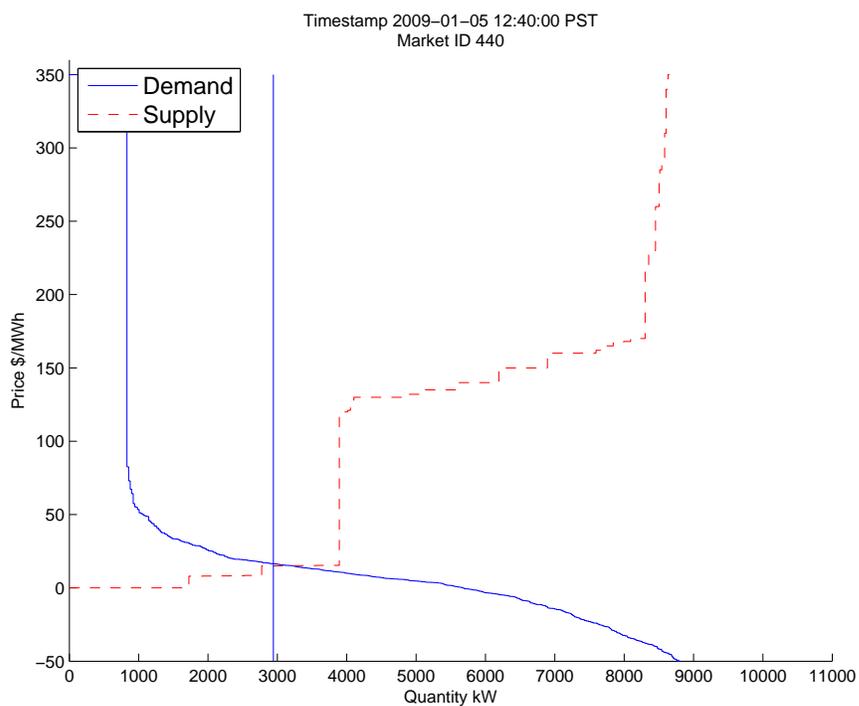


Figure 4.18: Market interaction with demand response and wind power

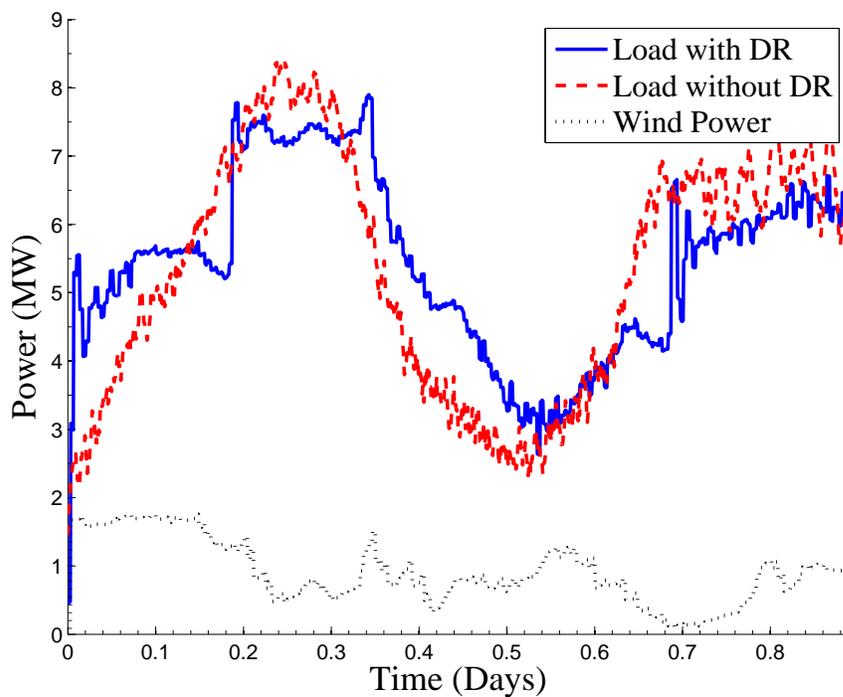


Figure 4.19: Comparison of load curves with and without demand response

## 4.4 Comparison of emissions

This section explores how demand response alters the behavior of individual generators in comparison to the base case scenarios without demand response. The changes in greenhouse gas emissions are determined using the methodology outlined in subsection 4.2.3.

### 4.4.1 Accumulated emissions

The effect on accumulated emissions over a period of one week can be seen in Fig. 4.20. The conclusion that can be drawn from the figure for the base case scenario is that demand response leads only to a slight decrease (approx. 5%) in GHG emissions when compared with the case in which there is no demand response. These quite unexpected results can be explained by the generation mix used in this specific simulation. High-price bidding, but low GHG-emitting, natural gas generation facilities are used as peaking power plants while low-price bidding, but high GHG-emitting coal power plants present the base load. Peak shaving events reduce and may even eliminate the need to utilize the natural gas power plants. However, following the peak event, loads switch on again due to the recharge/rebound effect described previously. Power usage is now higher than in the non-demand response scenario, at a time when less-expensive bidders, in this case coal power generating plants, are the marginal sellers defining the market price. The overall effect is for demand to shift from the peak of the curve, when low-emission plants are operative, to the valley when high-emission plants are operative. As a result only a relatively small decrease in GHG emissions is seen or, in a more extreme case, the additional high emission power production may lead to even higher GHG emissions. From these observations it is clear that the effect of demand response on GHG emissions is highly dependent on the generation mix.

When wind power is added into the generation mix then the emissions are almost the same at the end of the one week simulation period. In this case only low emitting gas generation is almost entirely displaced by wind power. However at the same time coal power is forced into a higher cycling and lower efficiency regimes.

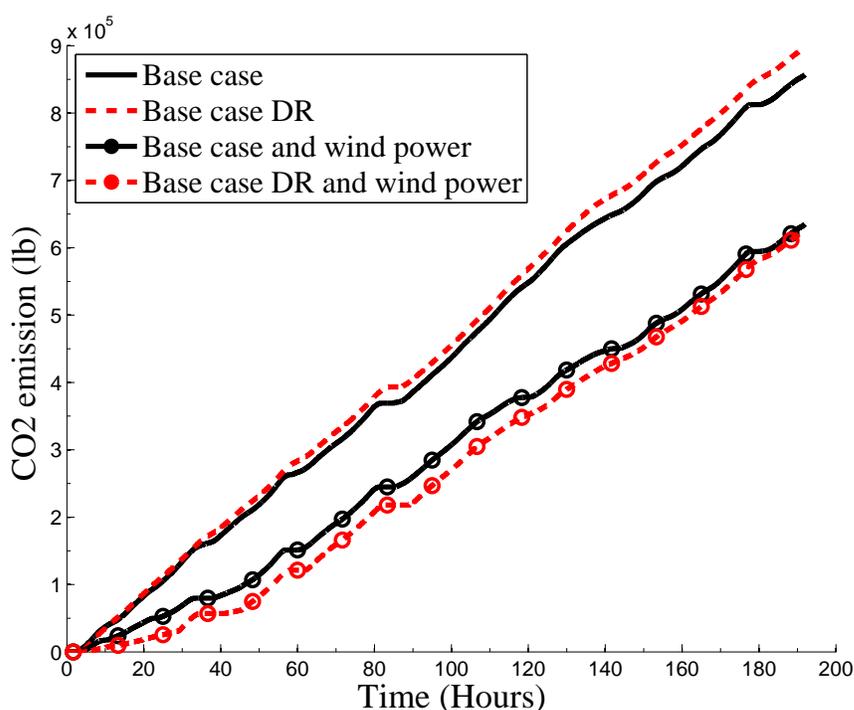


Figure 4.20: Comparison of accumulated emissions

#### 4.4.2 Individual emissions for fossil fuel based generators

In today's conventional electricity system high demand events often result in the recruitment of less efficient, or more carbon intensive peaking power plants to ensure that energy supply matches demand. These power plants are usually also the most expensive options for electricity generation, which is why they are kept in reserve.

In a demand response scenario high electricity prices during periods of peak loads will potentially reduce consumption and therefore costs. The effect is peak shaving and, in a best case scenario, it will neither be necessary to employ peaking power plants, nor, perhaps, to build and maintain them at all. In less optimal scenarios this will, at the very least, reduce the use of peaking power plants and, depending on the fuel used to generate electricity, possibly reduce GHG emissions.

Another positive side effect of demand response is a potential decrease in the need for capacity expansion in the transmission and distribution system, such as additional lines and transformers.

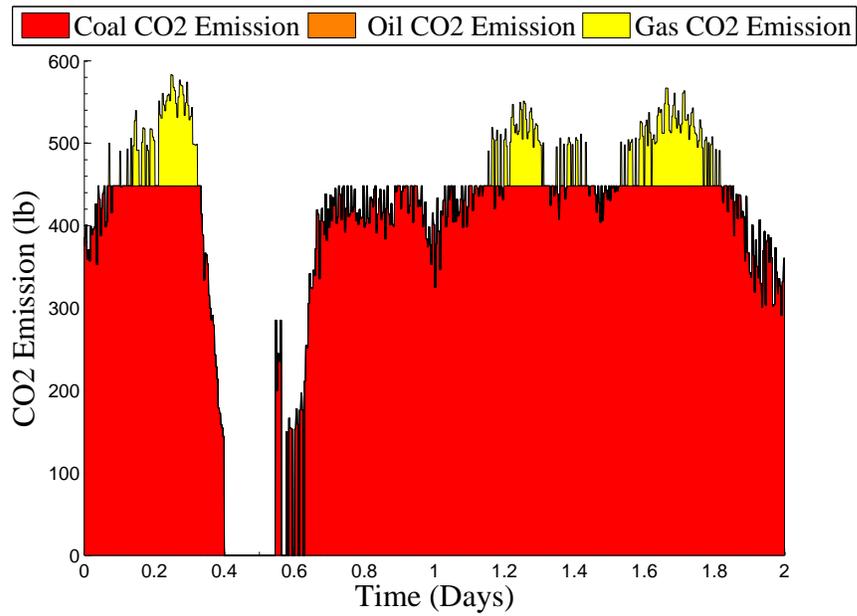


Figure 4.21: Base case: Emissions per fossil fuel based generator

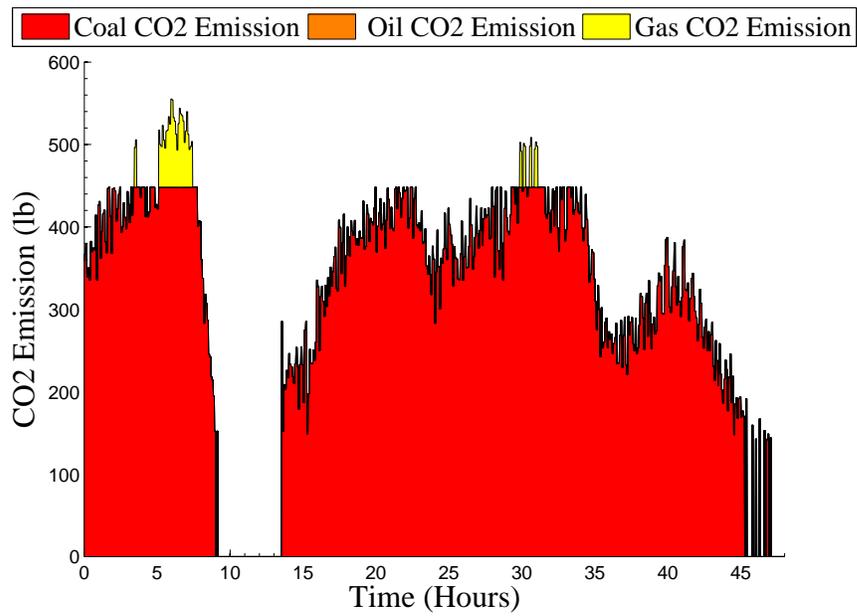


Figure 4.22: Base case and wind power: Emissions per fossil fuel based generator

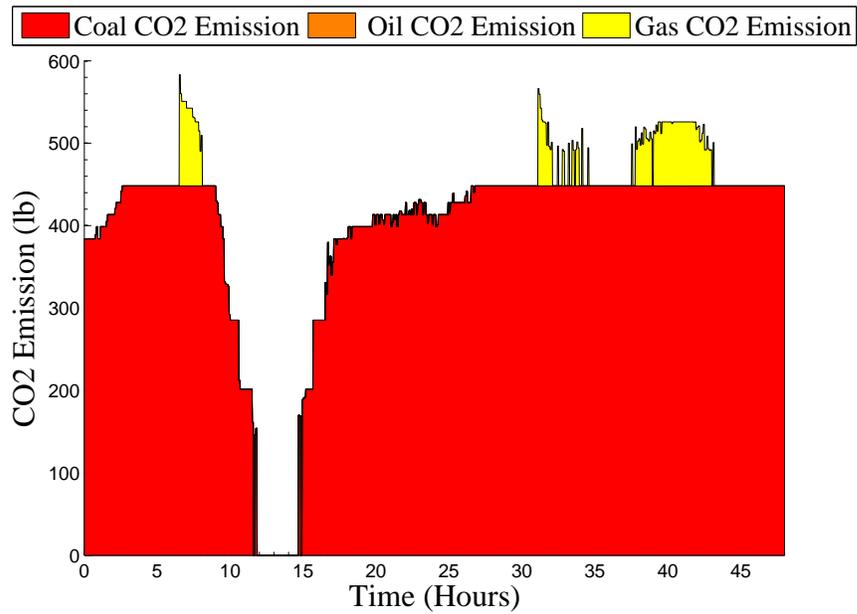


Figure 4.23: Base case and demand response: Emissions per fossil fuel based generator

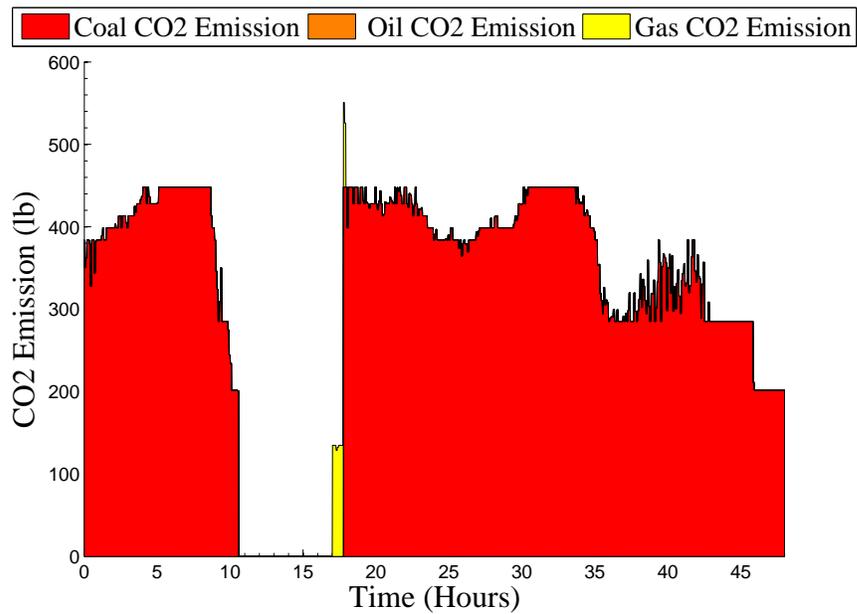


Figure 4.24: Base case, wind power and demand response: Emissions per fossil fuel based generator

#### 4.4.3 Emissions over time

The effect of peak shaving on emissions over a period of 24 hours can be seen in Fig. 4.25. Loads switch off during peak periods so that energy usage declines and, if

the peak generators are less-efficient and/or consume fossil fuels, GHG emissions will be reduced during these periods. However, figure Fig. 4.25 shows that peak shaving leads to a compensatory increase in energy usage after the peak, increasing emissions during those non-peak periods when compared to the non-demand response scenario. This so-called "rebound effect" show as "valley filling" on the emissions curve.

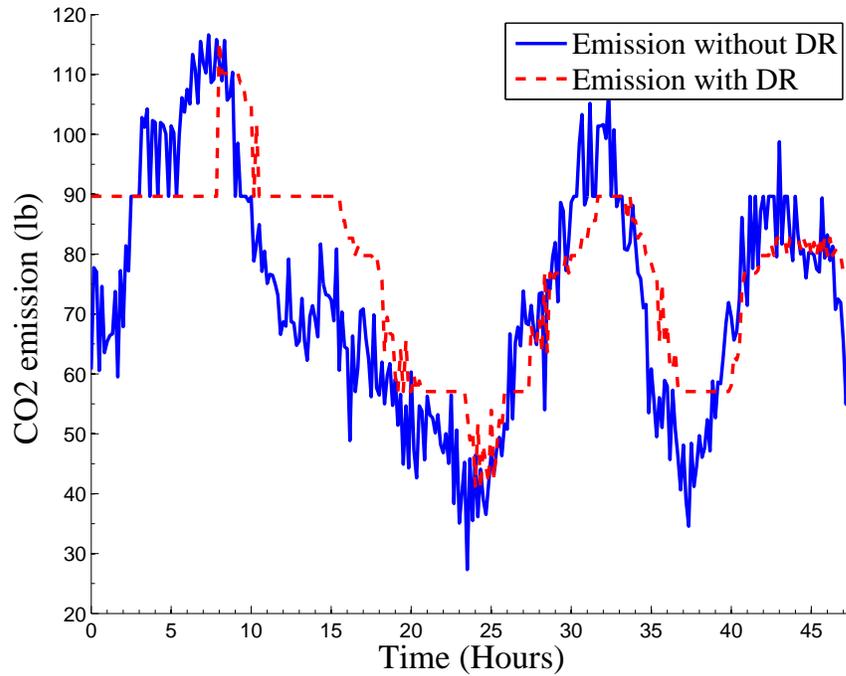


Figure 4.25: Comparison of emissions

## 4.5 Generator cycling

The increased utilization of variable renewable energy sources has well known positive effects, but, conversely, adds additional stresses to the power system. The increased net load variations from the incorporation of renewable energy suppliers such as wind power, requires other generators to react with more flexibility and, as a consequence, changes their cycling behaviour. Generally each additional generator cycling event is associated with additional cost, wear and tear, and increasing emissions. Furthermore, certain generation facilities such as nuclear and coal have limited flexibility of dispatchable generation and limited capability of cycling.

This section investigates how generator cycling is influenced by adding renewable energy (wind power) to the base case generation mix. Demand response is then added to the system and its potential to reduce generator cycling is examined.

The following figures show the accumulated cycling events for all generators over the same one week period and same conditions as the simulation cases outlined in the previous section.

### 4.5.1 Base case with and without wind power

Fig. 4.26 compares the accumulated cycling events with and without wind power.

In the base case scenario in Fig. 4.26 (a) the gas generation facility shows 111 cycle counts, as it compensates for most of the load variability. The oil generator cycles 8 times as it functions primarily as a peaking generator. Even the coal generator cycles 3 times over the week time span, as in these cases the total demand (low load events) can be fulfilled by hydro and nuclear power only.

The impact of adding wind power into the generation mix is shown in Fig. 4.26 (b). The oil generator that previously provided peaking power is now entirely displaced by wind power. Gas power generation is partly displaced, leading to a reduced cycle count of 58 for the gas generation facility. At the same time hydro plants start cycling (13 counts) and even coal power plants, that are not ideal candidates for cycling, are forced into cycling (6 counts). All of these effects are caused by wind power bidding with the lowest price of all generators and hence displacing, in part or completely, all of the remaining generators except nuclear.

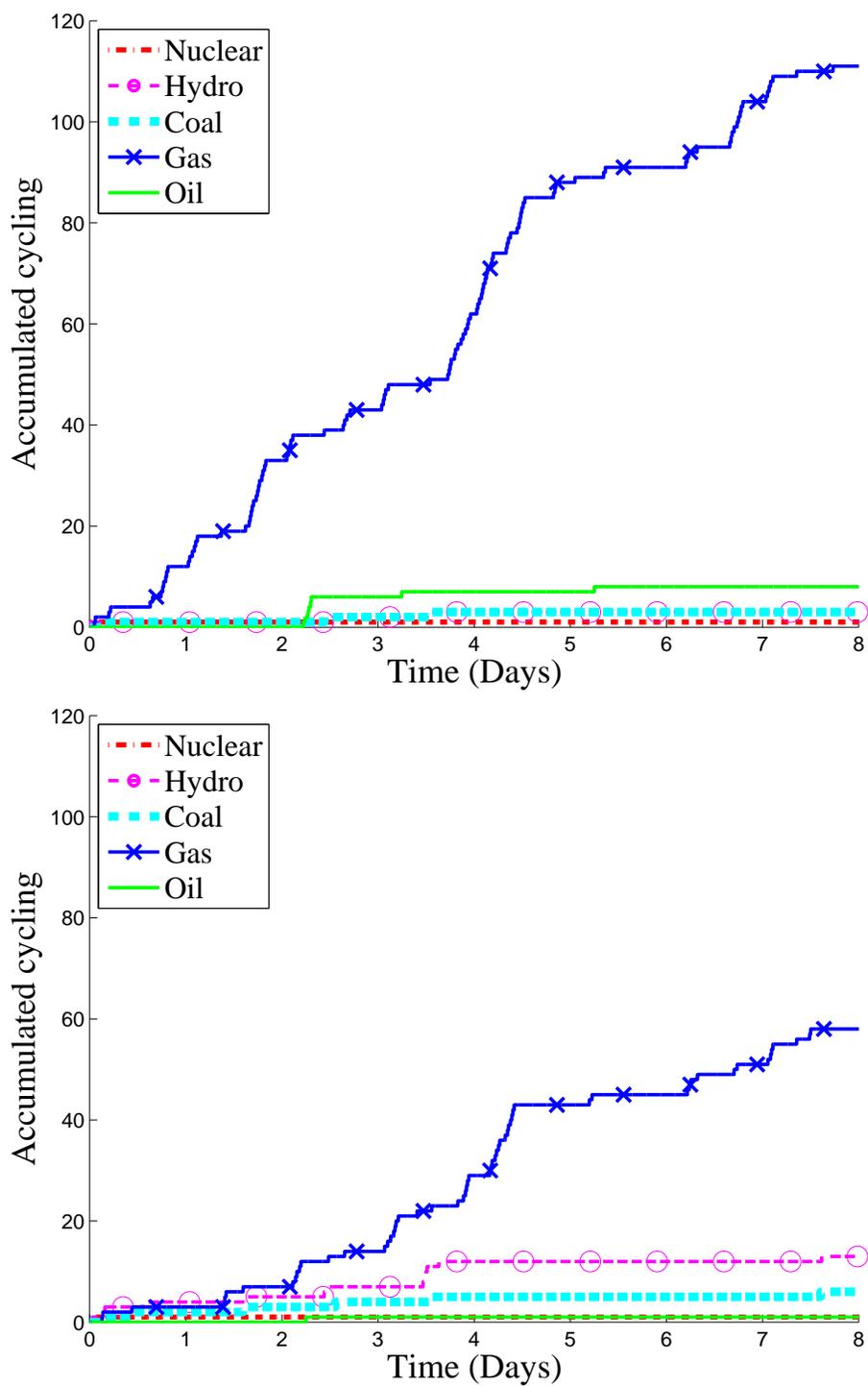


Figure 4.26: Accumulated generator cycling over a period of 1 week:  
 (a) Base case without wind power.  
 (b) Base case with wind power.

### 4.5.2 Adding demand response

Fig. 4.27 shows that, with or without wind power as part of the generation mix, demand response reduces the effect on cycling on the generators.

Fig. 4.27 (a) illustrates the positive effect of demand response on the base case scenario. The gas generation facility is now the only remaining power plant cycling, with a reduced cycle count of 7.

Fig. 4.27 (b) shows, how both wind power and demand response influence plant cycling. The gas generator cycle count is reduced to 5. Coal is only partly displaced by wind power, but the cycle count is reduced to 4.

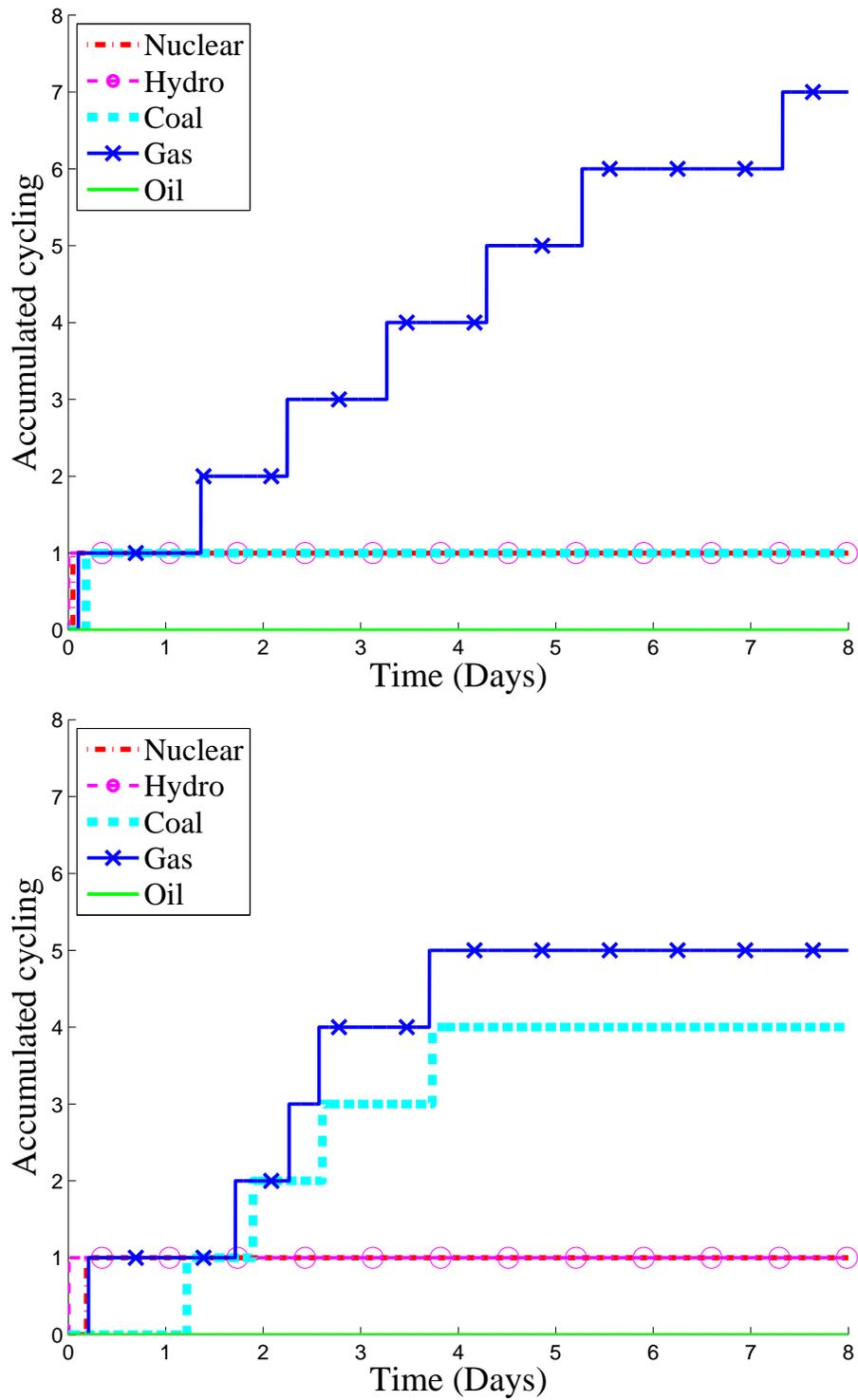


Figure 4.27: Accumulated generator cycling over a period of 1 week:  
 (a) Base case with demand response  
 (b) Base case with demand response and wind power

## 4.6 The limits of demand response and the "Battery state of charge"

This section will discuss the "limits of demand response". The contour plot in Fig. 4.28 represents the capabilities of all loads to participate in demand response activities during the total market period. The simulation was performed over a market period of one day and at a market interval of five minutes. The colors represent the bidding prices of households and correspond to the houses' inside temperatures. Blue colors indicate colder houses at the minimum set temperature and red colors indicate warmer houses at the maximum set temperature.

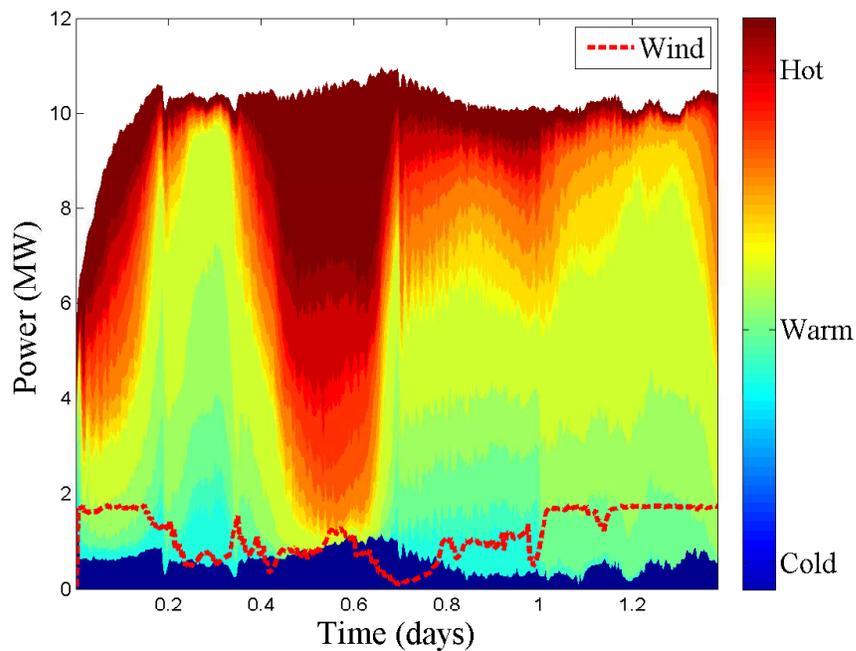


Figure 4.28: The battery state of charge

The plot reflects wind power surplus and deficits regimes and the transition states of the loads. It also can be referred to as the state of charge, according to terminology used for batteries and other storage devices. It shows that much of the behavior of demand response appears to the system as though it was energy storage. Unresponsive loads have no value for demand response. As an increasing number of responsive loads reach their predefined limits they become unresponsive. This may become become critical for the system, as demand response performance declines and eventually becomes ineffective. In order to mitigate these effects a diversity of loads have to be

part of the overall system.

## 4.7 Summary

This chapter investigated a smart grid power system incorporating 1,000 residential homes with electric heating appliances from the demand side and a generic generation mix representing the supply side. Wind power was added to the generation mix and changes to GHG emissions and generator cycling were monitored over one week for each market cycle. Results show that demand response has the potential to reduce GHG emissions and can mitigate generator cycling.

# Chapter 5

## Further Discussion and Conclusions

### 5.1 Summary of work

The first stage of this research was to create a smart grid power system model and then validate it using data from the Smart Grid Olympic Peninsula Demonstration Project. The agent based modeling and open source software, GridLAB-D, was utilized to design a model that represented the actual demonstration project. This model incorporated submodels of the transmission and distribution system, a real-time pricing electricity market, generator models, and a residential house model with all its appliances. Price signals and appliances controller were employed to make the demand side responsive and reacting on power surplus or deficits. The demand side within the Olympic Peninsula Demonstration Project was represented by four different groups of residential houses: a fixed group with no smart appliances, a Time-of-Use (TOU) group, a Real Time Pricing (RTP) group and a control group of non-participating houses. Furthermore, a commercial building was included on the demand side. This building was equipped with a back-up diesel generator with the ability to bid into the electricity market. Hence the building had the ability to disconnect from the grid. The supply side was based primarily on the Mid-Columbian wholesale market, but limited by a maximum feeder capacity of 750kW. A second supply option was available through a 30kW micro turbine.

The second stage of the research investigated the effects of adding wind power to the generation mix of the previously validated, but now scaled-up model. The new

system comprised 10,000 residential houses, a hydro electricity generation facility and a 35MW wind park. Results from the scaled-up system simulation showed that the load behavior of the individual houses changes, depending on wind power deficits and surplus.

The third and final stage of this work investigated the effects of both demand response and variable renewable energy sources (VRES) on the potential for mitigation of greenhouse gas emissions and on generator cycling. A generic generation mix was introduced, whereby nuclear, hydro, coal, gas and oil based generators are bidding into the electricity market. Wind power was added to this generation mix and the changes in GHG emissions and the generator state (on or off) monitored for each market cycle. The generator model incorporated the cost curve for each individual generator as well as start up and shutdown costs and minimum runtime. From the demand side 1,000 houses were bidding into the market, assuming that all had electric heating appliances equipped with the technology to react to market prices. A modified IEEE-4 feeder was used for simplicity of the grid topology and the simulation performed over a period of one week.

## 5.2 Results

A modeling and simulation framework was constructed and successfully used to validate a smart grid environment. The model allows the implementation of a large scale smart grid that includes complex transmission and distribution feeder topologies, several thousand residential houses with their appliances and controllers, and various generation supply options, all bidding into a common double auction electricity market. However, the size and complexity of the model requires significant computational power to solve the powerflow problem and for post-processing of simulation data.

The results derived from the simulations showed that smart grid technology and demand response can mitigate the already existing load variations, as well as the change in net load variations that are a consequence of the use of wind power and other renewable energy resources. Additionally it was found that the degree to which GHG emissions can be mitigated is highly dependent on the generation mix used. A displacement of natural gas based generation during peak demand could actually lead to an increase in GHG emissions if coal is used to generate the additional power required during the rebound period following peak power consumption.

Although the simulations have demonstrated that under certain conditions de-

mand response can lead to a small increase or only a marginal reduction of GHG emissions, demand response in principle can enhance the overall system operation. Positive outcomes are especially associated with the increased level of penetration of variable renewable electricity generation made possible by demand response and without jeopardizing grid operation reliability. Demand response can reduce the amount of generator cycling and ramping, reduce wear and tear on generating equipment, improve generator efficiency and avoid grid and generator capacity additions by shaving load peaks. Overall, this can facilitate increased use of renewable energy resources and as a consequence lead to a reduction of GHG emissions.

### **5.3 Perspective and future research**

Various power system models have been created and tested during this research. The following extends the discussion by providing a perspective on system aspects and some additional preliminary findings that were not discussed in the body of the dissertation but warrant further investigation.

#### **Increasing wind power penetration**

Within the current power system model, wind power bids with a price of \$0/MWh into the market to ensure that the electricity generated is sold. This bidding behavior becomes uneconomic with increasing wind penetration, to the point where high wind power combined with low load events could result in a market clearing prices of \$0/MWh. As a consequence the bidding strategy of wind power generators has to change with increasing wind power penetration and has to reflect the real cost of generation. However, this also may result in additional curtailment of wind power, as wind generators may be underbid by competing generators.

#### **Reserve requirements for wind power**

An increase in wind power penetration also requires a larger reserve capacity available to the power system. Preliminary results indicate that demand response can effectively mitigate the higher reserve requirements associated with wind power integration. The methodology described in [28], where standard deviation of the changes in demand and wind power generation is used to calculate operational reserve requirements for wind power, represents a validated and feasible approach for further

research in this area.

### **Generator model**

More detailed generator models are required that include ramp rates. Future models should also differentiate between cold, warm and hot starts of generators in order to more accurately determine the costs and emissions associated with generator cycling. While generator cycling is included in the current generator model by considering startup and shutdown cost, the on/off cycles are not considered for the accounting of emissions. However, each startup/shutdown sequence is also associated with additional fuel usage and hence increases GHG emission.

### **Grid issues**

For the purpose of simplifying the models used in this research an unconstrained grid was assumed. However, the model would also allow the investigation of grid issues such as feeder overload, voltage and frequency deviations.

### **Integrated energy system**

In the simulations conducted in this research the RTP double auction electricity market plays a key role in the operation of the overall system. Within this system all the individual agents, both generators and loads bid into the electricity market with their own individual goal. The goals of a thermostatic load, for example, are to buy power at the lowest price while ensuring that the desired temperature remains within a preset temperature range. However, satisfying only the goals of individual buyers and sellers might not guarantee the optimal performance and operation of the integrated power system. Additional regulatory factors or a "regulatory agent", that include both system objectives and constraints may be necessary to optimize the power system.

### **Other topics**

Another interesting extension of this research effort is forecasting, that could be included in the bidding strategy of sellers and buyers. Further investigation could also include the effects of RTP electricity markets on electricity prices.

# Appendix A

## Additional figures to Chapter 4

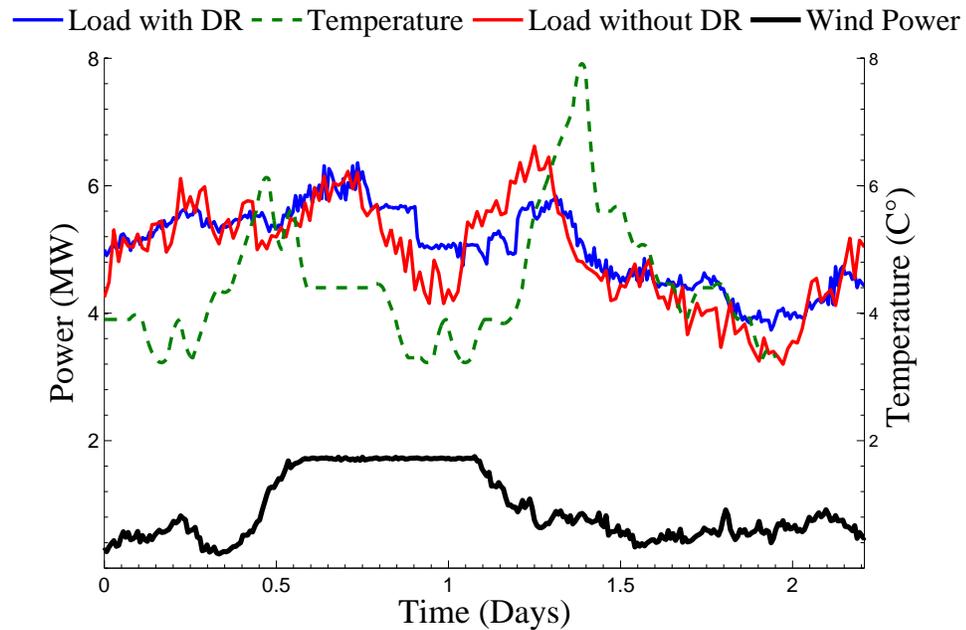


Figure A.1: Loadcurve of 1,000 residential houses without demand response, compared to the loadcurve with wind power and demand response

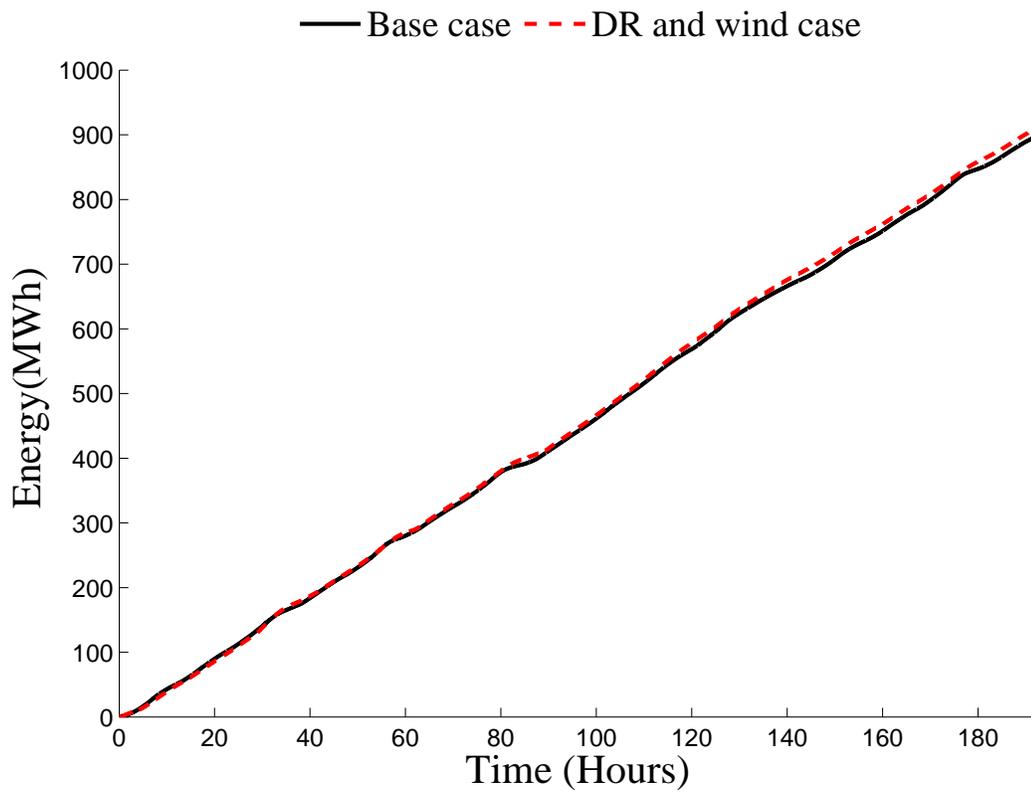


Figure A.2: Base case and demand response with wind power: comparison of energy use of all 1,000 residential houses

# Appendix B

## Technical implementation

### B.1 Further information

The following pages provide a programming overview and code. Additional information can be found under the following link: <http://www.engr.uvic.ca/~ndjilali/Broeer-supplementary.html>

## B.2 Programming overview

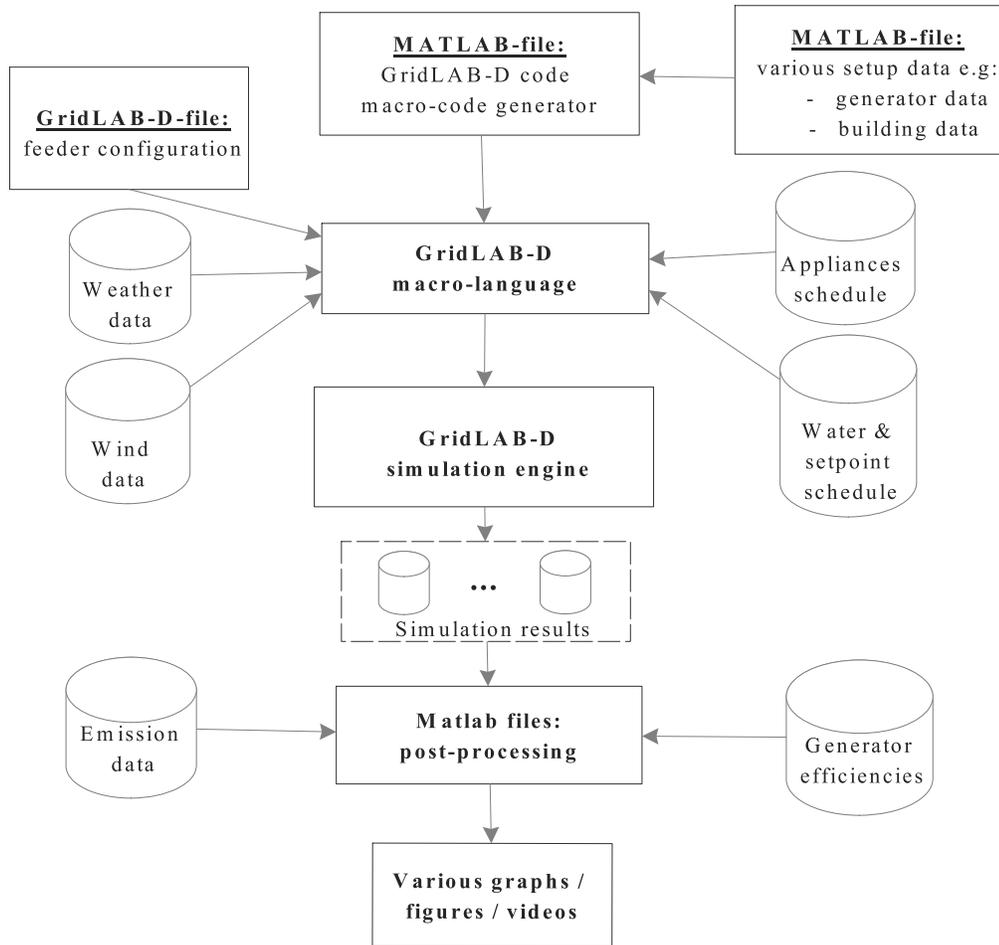


Figure B.1: Overview of programs, input- and output files

---

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## OVERVIEW: IEEE-4 feeder generator

Population script to add houses, generators and a market to a modified IEEE 4-node

Based on: Feeder\_Generator.m (open-source tool from PNNL)

Requires regionalization.m to be in the same folder

Last major modification: May 10, 2014

## Initialization / Prepare workspace

```
close all;
clear all;
clc;

%File name to output GridLAB-D Macro Language file(GLM)
FileOutput='C:\Sync_Notebook\Test_GLM_File.glm';

%base recorder name
BaseRecorderName='MarketTest';

%Number of houses to populate
NumHouses=1000;

%Minimum timestep (seconds)
MinTimeStep=60;

%Recorder interval
RecorderInterval=60;

%Market parameters
MarketPeriod=300;                               %market intervall = 5 minutes
MarketVerbose=0;
```

---

```

MarketPriceCap=350; %max. bid price = $3.5
MarketInitialPrice=50; %Statistics initialization
MarketInitialStdDev=10; %Statistics initialization
MarketCapacityReferenceBid=350;
MarketMaxCapacityReferenceQuantity=0;

%Time Parameters
StartTime='2009-01-04 00:00:00';
EndTime='2009-01-14 00:00:00';
TimeZone='PST+8PDT';

%Weather
WeatherFile='WA-Seattle.tmy2';

%Weather region
% 1 - West Coast - temperate
% 2 - North Central/Northeast - cold/cold
% 3 - Southwest - hot/arid
% 4 - Southeast/Central - hot/cold
% 5 - Southeast coastal - hot/humid
% 6 - Hawaii - sub-tropical (not part of original taxonomy)
WeatherRegion=1; % West coast weather (Seattle data)

%Want market controllers in the system?
%0 = none (no market), 1 = on
Want_Controllers=1;

%Want wind power in the system?
%0 = none, 1 = on
Want_Wind=1;

%Powerflow solver
%0 = FBS, 1 = NR
PowerflowSolver=1; % NR

%Pause at exit?
PauseAtExit=1;

%Initialize random stream
StreamVal = RandStream.create('mrg32k3a','NumStreams',1);

%Insure it is default
if ( verLessThan('matlab','8.1') )
    RandStream.setDefaultStream(StreamVal); %#ok<SETRS>
else
    RandStream.setGlobalStream(StreamVal);
end

%House phases
TempVar=rand(NumHouses,1);
HousePhaseAssignment=3*ones(NumHouses,1);
HousePhaseAssignment(TempVar<=0.33)=1;
HousePhaseAssignment((TempVar>0.33) & (TempVar<=0.67))=2;

```

---

```

%Get number of houses per phase
NumHousesPerPhase=[sum(HousePhaseAssignment==1)...
    sum(HousePhaseAssignment==2) sum(HousePhaseAssignment==3)];

%Pull region information
regional_data = regionalization(WeatherRegion);

% Create a histogram of what the thermal integrity of the houses should be
% Ceiling function will create a few extra houses in histogram, but its
% needed
thermal_integrity = ceil(regional_data.thermal_percentages * NumHouses);

total_houses_by_type = sum(thermal_integrity. ');

%only allow pool pumps on single family homes
no_pool_pumps = total_houses_by_type(1);

%Extract set point information
cool_sp = zeros(size(regional_data.cooling_setpoint{1}(:,1),1),3);
heat_sp = zeros(size(regional_data.heating_setpoint{1}(:,1),1),3);

for typeind=1:3
    cool_sp(:,typeind) = ceil(regional_data.cooling_setpoint{typeind}...
        (:,1) * total_houses_by_type(typeind));
    heat_sp(:,typeind) = ceil(regional_data.heating_setpoint{typeind}...
        (:,1) * total_houses_by_type(typeind));
end

%Large vs small percentage
TempValues=rand(NumHouses,1);
LargeVersusSmallValues=50*ones(NumHouses,1);
LargeVersusSmallValues(TempValues<=regional_data.percentageSmall)=-50;

```

## Set parameter

```

skew_value = regional_data.residential_skew_std*randn(NumHouses,1);
skew_value(skew_value < -regional_data.residential_skew_max) =...
    -regional_data.residential_skew_max;
skew_value(skew_value > regional_data.residential_skew_max) =...
    regional_data.residential_skew_max;

wh_skew_value = 3*regional_data.residential_skew_std*randn(NumHouses,1);
wh_skew_value(wh_skew_value < -6*regional_data.residential_skew_max) =...
    -6*regional_data.residential_skew_max;
wh_skew_value(wh_skew_value > 6*regional_data.residential_skew_max) =...
    6*regional_data.residential_skew_max;

% scale this skew up to weeks
pp_skew_value = 128*regional_data.residential_skew_std*randn(NumHouses,1);
pp_skew_value(pp_skew_value < -128*regional_data.residential_skew_max) =...
    -128*regional_data.residential_skew_max;
pp_skew_value(pp_skew_value > 128*regional_data.residential_skew_max) =...
    128*regional_data.residential_skew_max;

```

---

## \*\*\*\* Creating output file \*\*\*\*

### Headers

```
%open the file handle
fHandle=fopen(FileOutput,'wt');

%Start the initial matter
fprintf(fHandle,'//IEEE 4-node file - generated %s\n',...
    datestr(now,'yyyy-mm-dd HH:MM:SS'));
fprintf(fHandle,'//Generated with prefix '%s'\n',BaseRecorderName);
fprintf(fHandle,...
    '//Contained %d houses - [%d %d %d] in Weather Region %d\n',...
    NumHouses,NumHousesPerPhase(1),NumHousesPerPhase(2),...
    NumHousesPerPhase(3),WeatherRegion);
fprintf(fHandle,...
    '//Run with minimum_timestep=%d and recorders set at %d\n',...
    MinTimeStep,RecorderInterval);
if (Want_Controllers==1)
    fprintf(fHandle,['//Market ran with period=%d, price cap=%.2f,...
        'initial_price=%.2f, initial_std_dev=%.2f\n'],...
        MarketPeriod,MarketPriceCap,MarketInitialPrice,...
        MarketInitialStdDev);
    fprintf(fHandle,['//...and capacity reference bid=%.2f and max '...
        'capacity reference quantity=%.2f\n'],...
        MarketCapacityReferenceBid,MarketMaxCapacityReferenceQuantity);
    fprintf(fHandle,'//Controllers on all devices\n');
else
    fprintf(fHandle,['//Market ran with period=%d, price cap=%.2f,...
        'initial_price=%.2f, initial_std_dev=%.2f\n'],MarketPeriod,...
        MarketPriceCap,MarketInitialPrice,MarketInitialStdDev);
    fprintf(fHandle,['//and capacity reference bid=%.2f and max'...
        'capacity reference quantity=%.2f\n'],...
        MarketCapacityReferenceBid,MarketMaxCapacityReferenceQuantity);
    fprintf(fHandle,'//No Controllers\n');
end
if (PowerflowSolver==0)
    fprintf(fHandle,'//FBS Powerflow solver\n\n');
else
    fprintf(fHandle,'//NR Powerflow solver\n\n');
end

%Definitions
fprintf(fHandle,'#set suppress_repeat_messages=0\n');
fprintf(fHandle,'#set minimum_timestep=%d\n',MinTimeStep);
fprintf(fHandle,'#set profiler=1\n');
fprintf(fHandle,'#set randomseed=10\n');
if (PauseAtExit==1)
    fprintf(fHandle,'#set pauseatexit=1\n');
end
fprintf(fHandle,'#include "water_and_setpoint_schedule_v5.glm";\n');
fprintf(fHandle,'#include "appliance_schedules.glm";\n\n');
```

---

```

fprintf(fHandle, 'clock {\n'};
fprintf(fHandle, '\ttimezone %s;\n', TimeZone);
fprintf(fHandle, '\tstarttime ''%s'';\n', StartTime);
fprintf(fHandle, '\tstoptime ''%s'';\n', EndTime);
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'module tape;\n');
fprintf(fHandle, 'module climate;\n');
fprintf(fHandle, 'module market;\n');
fprintf(fHandle, 'module residential {\n'};
fprintf(fHandle, '\timplicit_enduses NONE;\n');
fprintf(fHandle, '}\n');
fprintf(fHandle, 'module powerflow {\n'};
if (PowerflowSolver==0)
    fprintf(fHandle, '\tsolver_method FBS;\n');
else
    fprintf(fHandle, '\tsolver_method NR;\n');
    fprintf(fHandle, '\tNR_iteration_limit 50;\n');
end
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'class auction {\n'};
fprintf(fHandle, '\tdouble current_price_mean_24h;\n');
fprintf(fHandle, '\tdouble current_price_stdev_24h;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object climate {\n'};
fprintf(fHandle, '\tname "WeatherData";\n');
fprintf(fHandle, '\ttmyfile "%s";\n', WeatherFile);
fprintf(fHandle, '\tinterpolate QUADRATIC;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, '#include "Test_Feeder_Line_Configurations.glm";\n\n');

```

## Auction object

```

if (Want_Controllers==1 || Want_Controllers==0)
    fprintf(fHandle, 'object auction {\n'};
    fprintf(fHandle, '\tname Market_1;\n');
    fprintf(fHandle, '\tperiod %d;\n', MarketPeriod);
    fprintf(fHandle, '\tunit kW;\n');
    if (MarketVerbose==1)
        fprintf(fHandle, '\tverbose TRUE;\n');
    end
    fprintf(fHandle, '\tspecial_mode NONE;\n');
    fprintf(fHandle, '\tprice_cap %f;\n', MarketPriceCap);
    fprintf(fHandle, '\tinit_price %f;\n', MarketInitialPrice);
    fprintf(fHandle, '\tinit_stdev %f;\n', MarketInitialStdDev);
    fprintf(fHandle, '\twarmup 0;\n');
    fprintf(fHandle, '\tcapacity_reference_object controller_9999;\n');
    fprintf(fHandle, '\tcapacity_reference_property power_out_real;\n');
    fprintf(fHandle, '\tcapacity_reference_bid_price %f;\n', ...
        MarketCapacityReferenceBid);
    fprintf(fHandle, '\tmax_capacity_reference_bid_quantity %f;\n', ...
        MarketMaxCapacityReferenceQuantity);
    fprintf(fHandle, '\tcurve_log_file "%s_market_bids.csv";\n', ...
        BaseRecorderName);

```

---

```

fprintf(fHandle, '\tcurve_log_info EXTRA;\n');
fprintf(fHandle, '\tobject recorder {\n');
fprintf(fHandle, ['\t\tproperty "current_market.clearing_price,...
    'current_market.clearing_quantity, fixed_price, fixed_quantity";\n']);
fprintf(fHandle, '\t\tinterval %d;\n', RecorderInterval);
fprintf(fHandle, '\t\tfile "%s_marketvalues.csv";\n', BaseRecorderName);
fprintf(fHandle, '\t};\n');
fprintf(fHandle, '}\n\n');
end

```

## IEEE-4 system with triplex

```

fprintf(fHandle, '////////////////////////////////////////\n');
fprintf(fHandle, '// BEGIN: IEEE-4 Feeder - main part\n');
fprintf(fHandle, '////////////////////////////////////////\n');
fprintf(fHandle, 'object node {\n');
fprintf(fHandle, '\tname node1;\n');
fprintf(fHandle, '\tphases "ABCN";\n');
fprintf(fHandle, '\tbustype SWING;\n');
fprintf(fHandle, '\tnominal_voltage 7200;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object overhead_line {\n');
fprintf(fHandle, '\tname ohl12;\n');
fprintf(fHandle, '\tphases "ABCN";\n');
fprintf(fHandle, '\tfrom node1;\n');
fprintf(fHandle, '\tto node2;\n');
fprintf(fHandle, '\tlength 2000;\n');
fprintf(fHandle, '\tconfiguration lc300;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object node {\n');
fprintf(fHandle, '\tname node2;\n');
fprintf(fHandle, '\tphases "ABCN";\n');
fprintf(fHandle, '\tnominal_voltage 7200;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object transformer {\n');
fprintf(fHandle, '\tname controller_9999;\n');
fprintf(fHandle, '\tphases "ABCN";\n');
fprintf(fHandle, '\tfrom node2;\n');
fprintf(fHandle, '\tto node3;\n');
fprintf(fHandle, '\tconfiguration tc400;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object node {\n');
fprintf(fHandle, '\tname node3;\n');
fprintf(fHandle, '\tphases "ABCN";\n');
fprintf(fHandle, '\tnominal_voltage 2400;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object overhead_line {\n');
fprintf(fHandle, '\tname ohl134;\n');
fprintf(fHandle, '\tphases "ABCN";\n');
fprintf(fHandle, '\tfrom node3;\n');
fprintf(fHandle, '\tto node4;\n');
fprintf(fHandle, '\tlength 2500;\n');
fprintf(fHandle, '\tconfiguration lc300;\n');

```

---

```

fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object node {\n');
fprintf(fHandle, '\tname node4;\n');
fprintf(fHandle, '\tphases "ABCN";\n');
fprintf(fHandle, '\tnominal_voltage 2400;\n');
fprintf(fHandle, '}\n\n');

```

## Load object for generators

```

fprintf(fHandle, '//Load object - for gen controller objects\n');
fprintf(fHandle, 'object load {\n');
fprintf(fHandle, '\tname gen_control_connect;\n');
fprintf(fHandle, '\tparent node1;\n');
fprintf(fHandle, '\tnominal_voltage 7200.0;\n');
fprintf(fHandle, '\tphases ABCN;\n');
fprintf(fHandle, '\tobject recorder {\n');
fprintf(fHandle, [\t\tproperty "constant_power_A,constant_power_B,...
    'constant_power_C';\n']);
fprintf(fHandle, [\t\tinterval %d;\n',RecorderInterval);
fprintf(fHandle, [\t\tfile "%s_generator_controller.csv";\n',...
    BaseRecorderName);
fprintf(fHandle, '\t};\n');
fprintf(fHandle, '}\n\n');

```

## Triplex portions

```

fprintf(fHandle, '////////////////////////////////////////\n');
fprintf(fHandle, '// BEGIN :Transformer and triplex_nodes\n');
fprintf(fHandle, '////////////////////////////////////////\n\n');
fprintf(fHandle, '//Triplex Transformers\n\n');
fprintf(fHandle, 'object transformer {\n');
fprintf(fHandle, '\tname center_tap_1;\n');
fprintf(fHandle, '\tphases AS;\n');
fprintf(fHandle, '\tfrom node4;\n');
fprintf(fHandle, '\tto trip_node_AS;\n');
fprintf(fHandle, '\tconfiguration AS_config;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object transformer {\n');
fprintf(fHandle, '\tname center_tap_2;\n');
fprintf(fHandle, '\tphases BS;\n');
fprintf(fHandle, '\tfrom node4;\n');
fprintf(fHandle, '\tto trip_node_BS;\n');
fprintf(fHandle, '\tconfiguration BS_config;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object transformer {\n');
fprintf(fHandle, '\tname center_tap_3;\n');
fprintf(fHandle, '\tphases CS;\n');
fprintf(fHandle, '\tfrom node4;\n');
fprintf(fHandle, '\tto trip_node_CS;\n');
fprintf(fHandle, '\tconfiguration CS_config;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, '//Triplex nodes\n\n');
fprintf(fHandle, 'object triplex_node {\n');

```

---

```

fprintf(fHandle, '\tname trip_node_AS;\n');
fprintf(fHandle, '\tphases AS;\n');
fprintf(fHandle, '\tnominal_voltage 120;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object triplex_node {\n');
fprintf(fHandle, '\tname trip_node_BS;\n');
fprintf(fHandle, '\tphases BS;\n');
fprintf(fHandle, '\tnominal_voltage 120;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object triplex_node {\n');
fprintf(fHandle, '\tname trip_node_CS;\n');
fprintf(fHandle, '\tphases CS;\n');
fprintf(fHandle, '\tnominal_voltage 120;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, '//Triplex meters\n\n');
fprintf(fHandle, 'object triplex_meter {\n');
fprintf(fHandle, '\tname trip_meter_AS;\n');
fprintf(fHandle, '\tphases AS;\n');
fprintf(fHandle, '\tnominal_voltage 120;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object triplex_meter {\n');
fprintf(fHandle, '\tname trip_meter_BS;\n');
fprintf(fHandle, '\tphases BS;\n');
fprintf(fHandle, '\tnominal_voltage 120;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object triplex_meter {\n');
fprintf(fHandle, '\tname trip_meter_CS;\n');
fprintf(fHandle, '\tphases CS;\n');
fprintf(fHandle, '\tnominal_voltage 120;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, '//Triplex lines\n\n');
fprintf(fHandle, 'object triplex_line {\n');
fprintf(fHandle, '\tname trip_line_AS;\n');
fprintf(fHandle, '\tphases AS;\n');
fprintf(fHandle, '\tfrom trip_node_AS;\n');
fprintf(fHandle, '\tto trip_meter_AS;\n');
fprintf(fHandle, '\tlength 10;\n');
fprintf(fHandle, '\tconfiguration triplex_line_configuration_1;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object triplex_line {\n');
fprintf(fHandle, '\tname trip_line_BS;\n');
fprintf(fHandle, '\tphases BS;\n');
fprintf(fHandle, '\tfrom trip_node_BS;\n');
fprintf(fHandle, '\tto trip_meter_BS;\n');
fprintf(fHandle, '\tlength 10;\n');
fprintf(fHandle, '\tconfiguration triplex_line_configuration_1;\n');
fprintf(fHandle, '}\n\n');
fprintf(fHandle, 'object triplex_line {\n');
fprintf(fHandle, '\tname trip_line_CS;\n');
fprintf(fHandle, '\tphases CS;\n');
fprintf(fHandle, '\tfrom trip_node_CS;\n');
fprintf(fHandle, '\tto trip_meter_CS;\n');
fprintf(fHandle, '\tlength 10;\n');
fprintf(fHandle, '\tconfiguration triplex_line_configuration_1;\n');

```



---

## Wind farm

```
if (Want_Wind==1)

fprintf(fHandle, '////////////////////////////////////////\n');
fprintf(fHandle, '//This represets a wind farm');
fprintf(fHandle, '////////////////////////////////////////\n');

fprintf(fHandle, 'object generator_controller {\n');
fprintf(fHandle, 'parent gen_control_connect;\n');
fprintf(fHandle, 'name gen_wind_power;\n');
fprintf(fHandle, 'market Market_1;\n');
fprintf(fHandle, 'generator_rating 1725.00;\n');
fprintf(fHandle, 'object player {\n');
fprintf(fHandle, 'file windpower.player;\n');
fprintf(fHandle, 'property bid_generator_rating; //generator_rating;\n');
fprintf(fHandle, '};\n');
fprintf(fHandle, 'generator_state OFF;\n');
fprintf(fHandle, 'bid_curve "1725.00 0";\n');
fprintf(fHandle, 'object player {\n');
fprintf(fHandle, 'file windpower_new.player;\n');
fprintf(fHandle, 'property bid_curve;\n');
fprintf(fHandle, '};\n');
fprintf(fHandle, 'object player {\n');
fprintf(fHandle, 'file windpower_bool.player;\n');
fprintf(fHandle, 'property "update_curve";\n');
fprintf(fHandle, '};\n');
fprintf(fHandle, 'object recorder {\n');
fprintf(fHandle, ['property "generator_output,generator_state,...
    'capacity_factor";\n']);
fprintf(fHandle, 'interval 60;\n');
fprintf(fHandle, 'file "gen_wind_power_output.csv";\n');
fprintf(fHandle, '};\n');
fprintf(fHandle, '};\n');
end
```

## Residential houses

```
%Common variables
building_type = {'Single Family'; 'Apartment'; 'Mobile Home'};

%Slider settings
% limit slider randomization to Olypen style
slider_random = 0.45 + (0.2).*randn(NumHouses,1);
    s11 = slider_random > regional_data.market_info;
slider_random(s11) = regional_data.market_info;
    s12 = slider_random < 0;
slider_random(s12) = 0;

fprintf(fHandle, '////////////////////////////////////////\n');
fprintf(fHandle, '//Houses\n');
fprintf(fHandle, '////////////////////////////////////////\n');
```

---

```

%Loop through the houses and output them
for hVals=1:NumHouses

    %Print first parts of house values
    fprintf(fHandle,'object house {\n'};
    fprintf(fHandle,'\tname house_%d;\n',hVals);
    if (HousePhaseAssignment(hVals)==1)
        fprintf(fHandle,'\tparent trip_meter_AS;\n');
    elseif (HousePhaseAssignment(hVals)==2)
        fprintf(fHandle,'\tparent trip_meter_BS;\n');
    else
        fprintf(fHandle,'\tparent trip_meter_CS;\n');
    end
    fprintf(fHandle,'\tgroupid Residential;\n');
    fprintf(fHandle,'\tschedule_skew %.0f;\n',skew_value(hVals));

    %Determine thermal integrity and floor area properties
    % Choose what type of building we are going to use
    % and set the thermal integrity of said building
    [size_a,size_b] = size(thermal_integrity);

    therm_int = ceil(size_a * size_b * rand(1));

    row_ti = mod(therm_int,size_a) + 1;
    col_ti = mod(therm_int,size_b) + 1;
    while ( thermal_integrity(row_ti,col_ti) < 1 )
        therm_int = ceil(size_a * size_b * rand(1));

        row_ti = mod(therm_int,size_a) + 1;
        col_ti = mod(therm_int,size_b) + 1;
    end

    thermal_integrity(row_ti,col_ti) = ...
        thermal_integrity(row_ti,col_ti) - 1;

    thermal_temp = regional_data.thermal_properties(row_ti,col_ti);

    f_area = regional_data.floor_area(row_ti);
    story_rand = rand(1);
    height_rand = randi(2);
    fa_rand = rand(1);
    if (col_ti == 1) % SF homes
        floor_area = f_area + (f_area/2) * fa_rand * (row_ti - 4)/3;
        if (story_rand < regional_data.one_story(WeatherRegion))
            stories = 1;
        else
            stories = 2;
        end
    else
        floor_area = f_area + (f_area/2) * (0.5 - fa_rand); %+/- 50%
        stories = 1;
        height_rand = 0;
    end
end

```

---

---

```

% Now also adjust square footage as a factor of whether
% the load modifier (avg_house) rounded up or down
floor_area = (1 + LargeVersusSmallValues(hVals)) * floor_area;

if (floor_area > 4000)
    floor_area = 3800 + fa_rand*200;
elseif (floor_area < 300)
    floor_area = 300 + fa_rand*100;
end

fprintf(fHandle, '\tfloor_area %.0f;\n', floor_area);
fprintf(fHandle, '\tnumber_of_stories %.0f;\n', stories);
ceiling_height = 8 + height_rand;
fprintf(fHandle, '\tceiling_height %.0f;\n', ceiling_height);
os_rand = regional_data.over_sizing_factor * (.8 + 0.4*rand);
fprintf(fHandle, '\tover_sizing_factor %.1f;\n', os_rand);
fprintf(fHandle, '\t//Thermal integrity -> %s %.0f\n', ...
    building_type{row_ti}, col_ti);

rroof = thermal_temp{1}(1)*(0.8 + 0.4*rand(1));
fprintf(fHandle, '\tRroof %.2f;\n', rroof);

rwall = thermal_temp{1}(2)*(0.8 + 0.4*rand(1));
fprintf(fHandle, '\tRwall %.2f;\n', rwall);

rfloor = thermal_temp{1}(3)*(0.8 + 0.4*rand(1));
fprintf(fHandle, '\tRfloor %.2f;\n', rfloor);
fprintf(fHandle, '\tglazing_layers %.0f;\n', thermal_temp{1}(4));
fprintf(fHandle, '\tglass_type %.0f;\n', thermal_temp{1}(5));
fprintf(fHandle, '\tglazing_treatment %.0f;\n', thermal_temp{1}(6));
fprintf(fHandle, '\twindow_frame %.0f;\n', thermal_temp{1}(7));

rdoor = thermal_temp{1}(8)*(0.8 + 0.4*rand(1));
fprintf(fHandle, '\tRdoors %.2f;\n', rdoor);
fprintf(fHandle, '\tRwindows 1.81;\n');

airchange = thermal_temp{1}(9)*(0.8 + 0.4*rand(1));
fprintf(fHandle, '\tairchange_per_hour %.2f;\n', airchange);

c_COP = thermal_temp{1}(11) + rand(1)*(thermal_temp{1}(10) - ...
    thermal_temp{1}(11));
fprintf(fHandle, '\tcooling_COP %.1f;\n', c_COP);

% set init_temp
init_temp = 69 + 4*rand(1);
fprintf(fHandle, '\tair_temperature %.2f;\n', init_temp);
fprintf(fHandle, '\tmass_temperature %.2f;\n', init_temp);

mass_floor = 2.5 + 1.5*rand(1);
fprintf(fHandle, '\tttotal_thermal_mass_per_floor_area %.3f;\n', ...
    mass_floor);

%Heating type information

```

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---

```

heat_type = rand(1);
cool_type = rand(1);
h_COP = c_COP;
ct = 'NONE';

if (heat_type <= regional_data.perc_gas)
    fprintf(fHandle, '\theating_system_type GAS;\n');
    if (cool_type <= regional_data.perc_AC)
        fprintf(fHandle, '\tcooling_system_type ELECTRIC;\n');
        ct = 'ELEC';
    else
        fprintf(fHandle, '\tcooling_system_type NONE;\n');
    end
    ht = 'GAS';
elseif (heat_type <= (regional_data.perc_gas + ...
    regional_data.perc_pump))
    fprintf(fHandle, '\theating_system_type HEAT_PUMP;\n');
    fprintf(fHandle, '\theating_COP %.1f;\n', h_COP);
    fprintf(fHandle, '\tcooling_system_type ELECTRIC;\n');
    fprintf(fHandle, '\tauxiliary_strategy DEADBAND;\n');
    fprintf(fHandle, '\tauxiliary_system_type ELECTRIC;\n');
    fprintf(fHandle, '\tmotor_model BASIC;\n');
    fprintf(fHandle, '\tmotor_efficiency AVERAGE;\n');
    ht = 'HP';
    ct = 'ELEC';

else
    fprintf(fHandle, '\theating_system_type RESISTANCE;\n');
    if (cool_type <= regional_data.perc_AC)
        fprintf(fHandle, '\tcooling_system_type ELECTRIC;\n');
        fprintf(fHandle, '\tmotor_model BASIC;\n');
        fprintf(fHandle, '\tmotor_efficiency GOOD;\n');
        ct = 'ELEC';
    else
        fprintf(fHandle, '\tcooling_system_type NONE;\n');
    end
    ht = 'ELEC';
end

%Breaker values
fprintf(fHandle, '\tbreaker_amps 1000;\n');
fprintf(fHandle, '\thvac_breaker_rating 1000;\n');

%Choose the heating and cooling schedule
cooling_set = ceil(regional_data.no_cool_sch*rand(1));
heating_set = ceil(regional_data.no_heat_sch*rand(1));

% choose a cooling bin
coolsp = regional_data.cooling_setpoint{row_ti};
[no_cool_bins, junk] = size(coolsp);

% see if we have that bin left
cool_bin = randi(no_cool_bins);
while (cool_sp(cool_bin, row_ti) < 1)

```

---

---

```

        cool_bin = randi(no_cool_bins);
    end
    cool_sp(cool_bin,row_ti) = cool_sp(cool_bin,row_ti) - 1;

    % choose a heating bin
    heatsp = regional_data.heating_setpoint{row_ti};
    [no_heat_bins,~] = size(heatsp);
    heat_bin = randi(no_heat_bins);
    heat_count = 1;

    % see if we have that bin left, then check to make sure
    % upper limit of chosen bin is not greater than lower limit
    % of cooling bin
    while (heat_sp(heat_bin,row_ti) < 1 || (heatsp(heat_bin,3) >= ...
        coolsp(cool_bin,4)))
        heat_bin = randi(no_heat_bins);

        if (heat_count > 20)
            heat_bin = 1;
            break;
        end

        heat_count = heat_count + 1;
    end
    heat_sp(heat_bin,row_ti) = heat_sp(heat_bin,row_ti) - 1;

    % randomly choose within the bin, then +/- one
    % degree to separate the deadbands
    cool_night = (coolsp(cool_bin,3) - coolsp(cool_bin,4))*rand(1) + ...
        coolsp(cool_bin,4) + 1;
    heat_night = (heatsp(heat_bin,3) - heatsp(heat_bin,4))*rand(1) + ...
        heatsp(heat_bin,4) - 1;

    cool_night_diff = coolsp(cool_bin,2) * 2 * rand(1);
    heat_night_diff = heatsp(heat_bin,2) * 2 * rand(1);

    %Remaining house properties
    fprintf(fHandle, '\thvac_power_factor 0.97;\n');
    fprintf(fHandle, '\tfan_type ONE_SPEED;\n');
    fprintf(fHandle, '\tnumber_of_doors 2;\n');

    fprintf(fHandle, '\tcooling_setpoint %.2f;\n',cool_night);

    fprintf(fHandle, '\theating_setpoint heating%d*%.2f+%.2f;\n',...
        heating_set,heat_night_diff,heat_night);

    %Controller writing
    if (Want_Controllers==1)
        fprintf(fHandle, '\tthermostat_deadband 0.001;\n');
        fprintf(fHandle, '\tdlc_offset 100;\n');

    % pull in the slider response level
    slider = slider_random(hVals);

```

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---

```

% set the pre-cool / pre-heat range to really small
% to get rid of it.
s_tstat = 6;
hrh = 1+5*(1-slider);
crh = 5-5*(1-slider);
hrl = -2.005+0*(1-slider);
crl = -0.005+0*(1-slider);

crh2 = s_tstat + (1 - slider) * (3 - s_tstat);
crl2 = s_tstat + (1 - slider) * (3 - s_tstat);

% below are the changed heating ramp settings
hrh2 = -s_tstat - (1 - slider); %* (3 - s_tstat); %!!! TB changed
hrl2 = -s_tstat - (1 - slider); %* (3 - s_tstat); %!!! TB changed

if (strcmp(ht,'HP') ~= 0) % Control both therm setpoints
fprintf(fHandle, '\tcooling_setpoint %.2f;\n',cool_night);
fprintf(fHandle, '\theating_setpoint %.2f;\n',cool_night-3);
fprintf(fHandle, '\tobject controller {\n');
fprintf(fHandle, '\t\ttschedule_skew %.0f;\n',skew_value(hVals));
fprintf(fHandle, '\t\ttbid_delay 1;\n');
fprintf(fHandle, '\t\ttname controller_%d;\n',hVals);
fprintf(fHandle, '\t\ttmarket Market_1;\n');
fprintf(fHandle, '\t\ttuse_override ON;\n');
fprintf(fHandle, '\t\ttoverride override;\n');
fprintf(fHandle, '\t\ttbid_mode ON;\n');
fprintf(fHandle, '\t\ttcontrol_mode DOUBLE_RAMP;\n');
fprintf(fHandle, '\t\ttresolve_mode DEADBAND;\n');
fprintf(fHandle, '\t\ttheating_range_high %.3f;\n',hrh);
fprintf(fHandle, '\t\ttcooling_range_high %.3f;\n',crh);
fprintf(fHandle, '\t\ttheating_range_low %.3f;\n',hrl);
fprintf(fHandle, '\t\ttcooling_range_low %.3f;\n',crl);
fprintf(fHandle, '\t\ttheating_ramp_high %.3f;\n',hrh2);
fprintf(fHandle, '\t\ttcooling_ramp_high %.3f;\n',crh2);
fprintf(fHandle, '\t\ttheating_ramp_low %.3f;\n',hrl2);
fprintf(fHandle, '\t\ttcooling_ramp_low %.3f;\n',crl2);
fprintf(fHandle, ['\t\ttcooling_base_setpoint '...
'cooling%d*%.2f+%.2f;\n'],cooling_set,cool_night_diff,...
cool_night);
fprintf(fHandle, ['\t\ttheating_base_setpoint '...
'heating%d*%.2f+%.2f;\n'],heating_set,heat_night_diff,...
heat_night);
fprintf(fHandle, '\t\ttperiod %d;\n',MarketPeriod);
fprintf(fHandle, '\t\ttaverage_target current_price_mean_24h;\n');
fprintf(fHandle, ['\t\ttstandard_deviation_target '...
'current_price_stdev_24h;\n']);
fprintf(fHandle, '\t\tttarget air_temperature;\n');
fprintf(fHandle, '\t\ttheating_setpoint heating_setpoint;\n');
fprintf(fHandle, '\t\ttheating_demand last_heating_load;\n');
fprintf(fHandle, '\t\ttcooling_setpoint cooling_setpoint;\n');
fprintf(fHandle, '\t\ttcooling_demand last_cooling_load;\n');

```

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---

```

fprintf(fHandle, '\t\tdeadband thermostat_deadband;\n');
fprintf(fHandle, '\t\ttotal hvac_load;\n');
fprintf(fHandle, '\t\tload hvac_load;\n');
fprintf(fHandle, '\t\tstate power_state;\n');
fprintf(fHandle, '\t};\n');
    elseif (strcmp(ht, 'ELEC') ~= 0) % Control heat, check if AC
        if (strcmp(ct, 'ELEC') ~= 0) % control like a heat pump

fprintf(fHandle, '\tcooling_setpoint %.2f;\n', cool_night);
        fprintf(fHandle, ['\theating_setpoint '...
            'heating%d*%.2f+%.2f;\n'], ...
            heating_set, heat_night_diff, heat_night);

fprintf(fHandle, '\tobject controller {\n');
fprintf(fHandle, '\t\tschedule_skew %.0f;\n', ...
        skew_value(hVals));
fprintf(fHandle, '\t\tbid_delay 1;\n');
fprintf(fHandle, '\t\tname controller_%d;\n', hVals);
fprintf(fHandle, '\t\tmarket Market_1;\n');
fprintf(fHandle, '\t\tuse_override ON;\n');
fprintf(fHandle, '\t\toverride override;\n');
fprintf(fHandle, '\t\tbid_mode ON;\n');
fprintf(fHandle, '\t\tcontrol_mode DOUBLE_RAMP;\n');
fprintf(fHandle, '\t\ttheating_range_high %.3f;\n', hrh);
fprintf(fHandle, '\t\tcooling_range_high %.3f;\n', crh);
fprintf(fHandle, '\t\ttheating_range_low %.3f;\n', hrl);
fprintf(fHandle, '\t\tcooling_range_low %.3f;\n', crl);
fprintf(fHandle, '\t\ttheating_ramp_high %.3f;\n', hrh2);
fprintf(fHandle, '\t\tcooling_ramp_high %.3f;\n', crh2);
fprintf(fHandle, '\t\ttheating_ramp_low %.3f;\n', hrl2);
fprintf(fHandle, '\t\tcooling_ramp_low %.3f;\n', crl2);
fprintf(fHandle, '\t\tcooling_base_setpoint 100;\n');
fprintf(fHandle, ['\theating_base_setpoint '...
            'heating%d*%.2f+%.2f;\n'], heating_set, ...
            heat_night_diff, heat_night);
fprintf(fHandle, '\t\tperiod %d;\n', MarketPeriod);
fprintf(fHandle, ['\t\taverage_target '...
            'current_price_mean_24h;\n']);
fprintf(fHandle, ['\t\tstandard_deviation_target '...
            'current_price_stdev_24h;\n']);
fprintf(fHandle, '\t\ttarget air_temperature;\n');
fprintf(fHandle, '\t\ttheating_setpoint heating_setpoint;\n');
fprintf(fHandle, '\t\ttheating_demand heating_demand;\n');
fprintf(fHandle, '\t\tcooling_setpoint cooling_setpoint;\n');
fprintf(fHandle, '\t\tcooling_demand last_cooling_load;\n');
fprintf(fHandle, '\t\tdeadband thermostat_deadband;\n');
fprintf(fHandle, '\t\ttotal total_load;\n');
fprintf(fHandle, '\t\tload hvac_load;\n');
fprintf(fHandle, '\t\tstate power_state;\n');
fprintf(fHandle, '\t};\n');
    else % control only the heat
fprintf(fHandle, '\tcooling_setpoint %.2f;\n', cool_night);
fprintf(fHandle, '\theating_setpoint %.2f;\n', cool_night-3);
fprintf(fHandle, '\tobject controller {\n');

```

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```

fprintf(fHandle, '\t\tsetpoint cooling_setpoint;\n');
fprintf(fHandle, '\t\tdemand last_cooling_load;\n');
fprintf(fHandle, '\t\tdeadband thermostat_deadband;\n');
fprintf(fHandle, '\t\ttotal hvac_load;\n');
fprintf(fHandle, '\t\tload hvac_load;\n');
fprintf(fHandle, '\t\tstate power_state;\n');
fprintf(fHandle, '\t};\n');
    else % gas heat, no AC, so no control
fprintf(fHandle, '\tcooling_setpoint cooling%d*%.2f+%.2f;\n',...
        cooling_set, cool_night_diff, cool_night);
fprintf(fHandle, '\theating_setpoint heating%d*%.2f+%.2f;\n',...
        heating_set, heat_night_diff, heat_night);

    end
end

%Auxilliary load pieces

% scale all of the end-use loads
scalar1 = 324.9/8907 * floor_area^0.442;
scalar2 = 0.8 + 0.4 * rand(1);
scalar3 = 0.8 + 0.4 * rand(1);
resp_scalar = scalar1 * scalar2;
unresp_scalar = scalar1 * scalar3;

% average size is 1.36 kW Energy Savings through Automatic Seasonal
% Run-Time Adjustment of Pool Filter Pumps Stephen D Allen, B.S.
% Electrical Engineering
pool_pump_power = 1.36 + .36*rand(1);
pool_pump_perc = rand(1);

% average 4-12 hours / day -> 1/6-1/2 duty cycle
% typically run for 2 - 4 hours at a time
pp_dutycycle = 1/6 + (1/2 - 1/6)*rand(1);
pp_period = 4 + 4*rand(1);
pp_init_phase = rand(1);

fprintf(fHandle, '\tobject ZIPload {\n');
fprintf(fHandle, '\t\t// Unresponsive load\n');
fprintf(fHandle, '\t\tname house_%d_unresp_load;\n', hVals);
fprintf(fHandle, '\t\ttschedule_skew %.0f;\n', skew_value(hVals));
fprintf(fHandle, '\t\tbase_power unresponsive_loads*%.2f;\n', ...
    unresp_scalar);
fprintf(fHandle, '\t\theatgain_fraction %.3f;\n', ...
    regional_data.heat_fraction);
fprintf(fHandle, '\t\tpower_pf %.3f;\n', regional_data.p_pf);
fprintf(fHandle, '\t\tcurrent_pf %.3f;\n', regional_data.i_pf);
fprintf(fHandle, '\t\timpedance_pf %.3f;\n', regional_data.z_pf);
fprintf(fHandle, '\t\timpedance_fraction %f;\n', ...
    regional_data.zfrac);
fprintf(fHandle, '\t\tcurrent_fraction %f;\n', regional_data.ifrac);
fprintf(fHandle, '\t\tpower_fraction %f;\n', regional_data.pfrac);
fprintf(fHandle, '\t};\n');

```

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## Regional and base data

```
% This function regionalization.m supplies regional and base data to the
% main program IEEE4_feeder_generator.m
```

```
function data = regionalization(region)

%Regional data that will be imported by the taxonomy script
% Regions:
% 1 - West Coast - temperate
% 2 - North Central/Northeast - cold/cold
% 3 - Southwest - hot/arid
% 4 - Southeast/Central - hot/cold
% 5 - Southeast coastal - hot/humid
% 6 - Hawaii - sub-tropical (not part of original taxonomy)
```

## Regional building data

TODO: Region 6 is unknown right now thermal\_percentage integrity percentages {region}(level,sf/apart/mh) single family homes apartments mobile homes level corresponds to age of home from "Building Reccs" 1:pre-1940, 2:1940-1949, 3:1950-1959, 4:1960-1969, 5:1970-1979, 6:1980-1989, 7:1990-2005 1:pre-1960, 2:1960-1989, 3:1990-2005 1:pre-1960, 2:1960-1989, 3:1990-2005

```
thermal_percentage{1} = [0.0805,0.0724,0.1090,0.0867,0.1384,0.1264,0.1297;
                        0.0356,0.1223,0.0256,0.0000,0.0000,0.0000,0.0000;
                        0.0000,0.0554,0.0181,0.0000,0.0000,0.0000,0.0000];
thermal_percentage{2} = [0.1574,0.0702,0.1290,0.0971,0.0941,0.0744,0.1532;
                        0.0481,0.0887,0.0303,0.0000,0.0000,0.0000,0.0000;
                        0.0000,0.0372,0.0202,0.0000,0.0000,0.0000,0.0000];
thermal_percentage{3} = [0.0448,0.0252,0.0883,0.0843,0.1185,0.1315,0.2411;
                        0.0198,0.1159,0.0478,0.0000,0.0000,0.0000,0.0000;
                        0.0000,0.0524,0.0302,0.0000,0.0000,0.0000,0.0000];
thermal_percentage{4} = [0.0526,0.0337,0.0806,0.0827,0.1081,0.1249,0.2539;
                        0.0217,0.1091,0.0502,0.0000,0.0000,0.0000,0.0000;
                        0.0000,0.0491,0.0333,0.0000,0.0000,0.0000,0.0000];
thermal_percentage{5} = [0.0526,0.0337,0.0806,0.0827,0.1081,0.1249,0.2539;
                        0.0217,0.1091,0.0502,0.0000,0.0000,0.0000,0.0000;
                        0.0000,0.0491,0.0333,0.0000,0.0000,0.0000,0.0000];
thermal_percentage{6} = [0.0526,0.0337,0.0806,0.0827,0.1081,0.1249,0.2539;
                        0.0217,0.1091,0.0502,0.0000,0.0000,0.0000,0.0000;
                        0.0000,0.0491,0.0333,0.0000,0.0000,0.0000,0.0000];

for jjj=1:6
```

---

```

    check_total = sum(sum(thermal_percentage{jjj}));
    if ( abs(check_total - 1) > 0.001 )
        error(['Error in total thermal_percentage{',num2str(jjj),...
            '}' - Sum does not equal 100%.']);
    end
end

% thermal properties for each level
% {sf/apart/mh,level}(R-ceil,R-wall,R-floor>window layers>window glass,
% glazing treatment, window frame, R-door, Air infiltration, COP high,
% COP low) Single family homes
thermal_properties{1,1} = [16.0, 10.0, 10.0, 1, 1, 1, 1, 3, .75,...
    2.8, 2.4];
thermal_properties{1,2} = [19.0, 11.0, 12.0, 2, 1, 1, 1, 3, .75,...
    3.0, 2.5];
thermal_properties{1,3} = [19.0, 14.0, 16.0, 2, 1, 1, 1, 3, .5,...
    3.2, 2.6];
thermal_properties{1,4} = [30.0, 17.0, 19.0, 2, 1, 1, 2, 3, .5,...
    3.4, 2.8];
thermal_properties{1,5} = [34.0, 19.0, 20.0, 2, 1, 1, 2, 3, .5,...
    3.6, 3.0];
thermal_properties{1,6} = [36.0, 22.0, 22.0, 2, 2, 1, 2, 5, 0.25,...
    3.8, 3.0];
thermal_properties{1,7} = [48.0, 28.0, 30.0, 3, 2, 2, 4, 11, 0.25,...
    4.0, 3.0];
% Apartments
thermal_properties{2,1} = [13.4, 11.7, 9.4, 1, 1, 1, 1, 2.2, .75,...
    2.8, 1.9];
thermal_properties{2,2} = [20.3, 11.7, 12.7, 2, 1, 2, 2, 2.7, 0.25,...
    3.0, 2.0];
thermal_properties{2,3} = [28.7, 14.3, 12.7, 2, 2, 3, 4, 6.3, .125,...
    3.2, 2.1];
% Mobile Homes
thermal_properties{3,1} = [ 0, 0, 0, 0, 0, 0, 0, 0, 0,...
    0, 0];
thermal_properties{3,2} = [13.4, 9.2, 11.7, 1, 1, 1, 1, 2.2, .75,...
    2.8, 1.9];
thermal_properties{3,3} = [24.1, 11.7, 18.1, 2, 2, 1, 2, 3, .75,...
    3.5, 2.2];

% Average floor areas for each type and region
% TODO: Region 6 is unknown right now
floor_area{1} = [2209,820,1054];
floor_area{2} = [2951,798,1035];
floor_area{3} = [2370,764,1093];
floor_area{4} = [2655,901,1069];
floor_area{5} = [2655,901,1069];
floor_area{6} = [2655,901,1069];

% Percentage of one-story homes
% TODO: Region 6 is unknown right now
one_story = [.6887;.5210;.7745;.7043;.7043;.7043];

% Average heating and cooling setpoints

```

---

---

```

% by thermal integrity type {1=SF, 2=apt, 3=mh} [nighttime percentage,
% nighttime average difference (+ indicates nighttime is cooler), high bin
% value, low bin value]
cooling_setpoint{1} = [ 0.098,0.96,69,65;
                      0.140,0.96,70,70;
                      0.166,0.96,73,71;
                      0.306,0.96,76,74;
                      0.206,0.96,79,77;
                      0.084,0.96,85,80];

cooling_setpoint{2} = [ 0.155,0.49,69,65;
                      0.207,0.49,70,70;
                      0.103,0.49,73,71;
                      0.310,0.49,76,74;
                      0.155,0.49,79,77;
                      0.069,0.49,85,80];

cooling_setpoint{3} = [ 0.138,0.97,69,65;
                      0.172,0.97,70,70;
                      0.172,0.97,73,71;
                      0.276,0.97,76,74;
                      0.138,0.97,79,77;
                      0.103,0.97,85,80];

heating_setpoint{1} = [ 0.141,0.80,63,59;
                       0.204,0.80,66,64;
                       0.231,0.80,69,67;
                       0.163,0.80,70,70;
                       0.120,0.80,73,71;
                       0.141,0.80,79,74];

heating_setpoint{2} = [ 0.085,0.20,63,59;
                       0.132,0.20,66,64;
                       0.147,0.20,69,67;
                       0.279,0.20,70,70;
                       0.109,0.20,73,71;
                       0.248,0.20,79,74];

heating_setpoint{3} = [ 0.129,0.88,63,59;
                       0.177,0.88,66,64;
                       0.161,0.88,69,67;
                       0.274,0.88,70,70;
                       0.081,0.88,73,71;
                       0.177,0.88,79,74];

% Breakdown of gas vs. heat pump vs. resistance - by region
% TODO: Region 6 is unknown right now
perc_gas = [0.00051;0.8927;0.6723;0.4425;0.4425;0.4425];
perc_pump = [0.0000;0.0177;0.0559;0.1983;0.1983;0.1983];
perc_res = 1 - perc_pump - perc_gas;

% of AC
% TODO: Region 6 is unknown right now
perc_AC = [1;0.7528;0.5259;0.9673;0.9673;0.9673];

```

---

---

```

% Over sizing factor of the AC units
% TODO: Region 6 is unknown right now
over_sizing_factor = [0.1;0.2;0.2;0.3;0.3;0.3];

% pool pumps
% TODO: Region 6 is unknown right now
perc_poolpumps = [0.0904;0.0591;0.0818;0.0657;0.0657;0.0657];

% water heaters
% Breakdown by fuel vs. electric
% TODO: Region 6 is unknown right now
wh_electric = [0.7455;0.7485;0.6520;0.3572;0.3572;0.3572];

% size of units - [<30, 31-49, >50] - by region
% TODO: Region 6 is unknown right now
wh_size = [ 0.0000,0.3333,0.6667;
            0.1459,0.5836,0.2706;
            0.2072,0.5135,0.2793;
            0.2259,0.5267,0.2475;
            0.2259,0.5267,0.2475;
            0.2259,0.5267,0.2475];

% emission dispatch order
% Nuc Hydro Solar BioMass Wind Coal NG GeoTherm Petro
% TODO: Region 6 is unknown right now
dispatch_order = [1,5,2,3,4,7,6,8,9;
                  1,7,2,3,4,5,6,8,9;
                  1,7,2,3,4,5,6,8,9;
                  1,7,2,3,4,5,6,8,9;
                  1,7,2,3,4,6,5,8,9;
                  1,7,2,3,4,6,5,8,9];

data.thermal_properties = thermal_properties;
data.thermal_percentages = thermal_percentage{region};
data.cooling_setpoint = cooling_setpoint;
data.heating_setpoint = heating_setpoint;
data.perc_gas = perc_gas(region);
data.perc_pump = perc_pump(region);
data.perc_res = perc_res(region);
data.perc_AC = perc_AC(region);
data.perc_poolpumps = perc_poolpumps(region);
data.floor_area = floor_area{region};
data.perc_poolpumps = perc_poolpumps(region);
data.wh_electric = wh_electric(region);
data.wh_size = wh_size(region,:);
data.no_cool_sch = 8;
data.no_heat_sch = 6;
data.no_water_sch = 6;
data.one_story = one_story;
data.over_sizing_factor = over_sizing_factor(region);
data.dispatch_order = dispatch_order(region,:);

```

---

---

```

%Other parameters

%Percentage small homes on the feeder (versus large homes)
data.percentageSmall=0.50;

% Skews
data.residential_skew_std = 2700;
data.residential_skew_max = 8100;
data.commercial_skew_std = 1800; %These are in 30 minute blocks
data.commercial_skew_max = 5400;

```

```

Error using regionalization (line 191)
Not enough input arguments.

```

## Residential parameters / technology parameters

ZIP fractions and their power factors - Residential

```

data.z_pf = 1;
data.i_pf = 1;
data.p_pf = 1;
data.zfrac = 0.2;
data.ifrac = 0.4;
data.pfrac = 1 - data.zfrac - data.ifrac;

data.heat_fraction = 0.9;

% waterheaters 1 = yes, 0 = no
data.use_wh = 1;
data.res_meter_cons = 0;

%Slider setting-related item from technology file
data.market_info=1.0;

% There is no ZIP fraction associated with this variable
data.light_scalar_res = 1;

```

## Generator controller data

```

%Generator controller object information
% { rating (kW), start state, bid_curve text, startup cost, shutdown_cost,
% min runtime, min downtime, amortizaiton factor (1/h)}

data.GenControlInformation = {
    {1050, 'OFF', '200 8.00 400 8.1 600 8.2 800 8.3 1050 8.5',...
    55.00, 55.00, 360.0, 0.0, 5}; %Nuclear
    {1120, 'OFF', '200 15.00 400 15.1 600 15.2 800 15.3 1120 15.4',...
    15.00, 15.00, 5.0, 0.0, 5}; % Hydro
    {2940, 'OFF', ['200 20.00 400 22.00 700 25.00 1200 30 1800 40 2500 50'...
    '2600 52 2700 55 2800 58.0 2940 60.00'],...
    55.00, 55.00, 240.0, 0.0, 5}; %Coal

```

---

```
{1470, 'OFF', ['120 70.00 160 71.00 210 78 800 80 1000 85 1100 90'...  
'1200 100 1250 115 1400 117 1470 120.00'],...  
25.00, 25.00, 30.0, 0.0, 5}; %Gas  
{420, 'OFF', ['50 140.00 150 150 200 180 210 200 240 205 280 210'...  
'300 230 330 260 400 280.0 420 350.00'],...  
40.00, 40.00, 30.0, 0.0, 5}; %Oil  
};
```

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