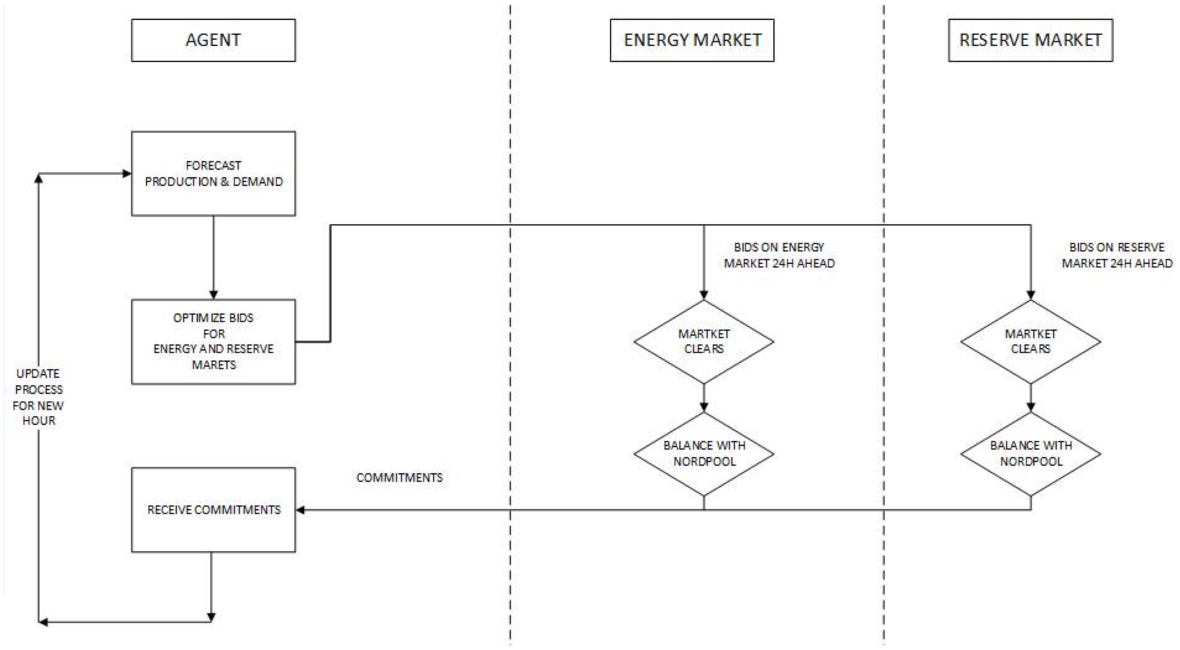

Design and modeling of a local energy market

A case study of Chalmers campus

Master's thesis in Sustainable Energy System

Philip Sjöstrand & Rickard Zäther
Department of Electric Engineering
Division of Electric Power Engineering
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2017

MASTER'S THESIS 2017:NN

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PHILIP SJÖSTRAND & RICKARD ZÄTHER

Supervisor and examiner: Anh Tuan Le, Department of Electric Engineering

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Department of Electric Engineering
Division of Electric Power Engineering

Chalmers University of Technology
SE-412 96 Gothenburg
Telephone +46 31 772 1000

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Rickard Zäther
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Abstract

The possibility with micro grids, smart energy buildings, customers with photovoltaic, storage or demand flexibility enables new opportunities for the energy system. This thesis is done in collaboration with an on-going-EU-funded project - Fossil- Free Energy District (FED), where Chalmers is one of the partners. The project aims to design and model a local energy market to establish what financial and energy gain there might be. This thesis sets out to design a local energy market, implement it in a computational model and simulate how this behaves during different scenarios.

A model for a local energy market has therefore been developed. The designed model is based on theory from energy markets as well as previous attempts to design a local energy market. The designed market has the possibility to trade both energy and reserve energy. The reason for this is to have the possibility to handle the inevitable demand and supply commitment errors made on the market ahead of delivery. The reserve market then balances the local energy market to deal with this issue. The model has then been implemented in GAMS with the purpose to simulate how the market would behave in different scenarios.

The result from the computational model showed how the market players is able to trade both energy and reserve energy. The increase in energy equipment did not give a noticeable difference in energy traded but a major increase in reserve energy. The amount of energy traded was about 10% of the total demand in the local energy market throughout all scenarios. The market was therefor highly dependent on the grid to provide the rest. The amount of reserve energy provided was increased with about 45% if comparing the scenario with the least amount of energy equipment installation compared with the one with the most. The results illustrated how forecast errors, both regarding production and consumption, could use the reserves to balance their needs. The model results also showcase the problems, mainly with the price relations, occurring when it is integrated with other energy market such as Nordpool. The price of energy on the local energy market are very dependent of the intelligence obtained by the market players. If the market should be efficient, every market player needs to actively participating and every market player also needs to make wise decisions. Since these decisions are based on forecast, the intelligence required by the market players to make these is very high.

Keywords: Local Energy Market, Energy Market, Demand and Response , Solar PV , OPF, CHP, Market Clearing Price , Energy Storage.

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Philip Sjöstrand & Rickard Zäther, Gothenburg, August 2017

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Nomenclature

Abbreviations

PV	Photovoltaics.
CHP	Combined Heat and Power.
DNI	Direct Normal Irradiance.
DNI$_{STC}$	Direct Normal Irradiance Standard Test Condition.
ESS	Energy Storage System.
EV	Electric vehicle.
FES	Flywheel Energy Storage.
GAMS	General Algebraic Modeling System.
LEM	Local Energy Market.
OPF	Optimal Power Flow.
SOC	State of Charge.

Symbols

α	Heat-to-power ratio.
η_{chr}	Charge efficiency.
η_{dis}	Discharge efficiency.
$\theta_{i,j}$	Angle associated with admittance matrix element of i and j
CO_E	Cost of selling energy.
CO_S	Cost of sellin reserve energy.
DB	Demand Bids
DB_s	Demand Bids for reserve energy
Dem	Demand and respons.
E	Energy.
E_{rated}	Installed battery capacity.
Exp	Amount of energy exported.
GF	Grid fee.
h	Hour.
IC_E	Forecasted income.
IC_S	Income from selling reserve energy
Imp	Amount of energy imported.
K	Probability of the reserve being used.
$Loss$	Losses in the system.
P_{bat}	Amount of energy from battery.
$P_{CHP,real}$	The actual amount of CHP production
P_{heat}	Amount of heat produced.
P_{load}	Demand from each agent.
P_{min}	Minimum amount of energy for the CHP

P_{prod}	Production from each agent.
P_{pv}	Solar output power.
P_{rated}	Rated output power.
$P_{respons}$	Amount of energy an agent offers in demand response.
P_{res}	Available reserve energy.
P_{sund}	Amount of solar energy produced.
P_{wr}	Amount of energy imported.
Pb_s	Amount of reserve energy market clears
$Pedy$	Amount of reserved energy from Battery.
$PPSe$	Price for being reserve.
Pri	Forecasted electricity price.
$Prsesp$	Amount of reserved energy from demand response.
$Pryr$	Price for being inactive reserve.
PS_e	Amount of reserved energy from CHP.
$Rdown$	Ramp down.
Rup	Ramp up.
S_{heat}	Amount of sold heat.
W1	Binary number, indicating CHP is on or off.

1

Introduction

1.1 Background and Motivations

The possibility with micro grids, smart energy buildings, customers with photovoltaic, storage or demand flexibility enables new opportunities for the local energy market and their participants. Instead of exporting power back to the utility grid, different actors could trade with each other in their local surroundings. For this type of trading a new type of framework have to be developed, this is called local energy markets [1]. A local energy market is an auction-based online platform that allows market participants, known as “players”, within a certain area, to trade energy with each other [2].
The benefits from local energy markets are many, including e.g. result in cost savings on the electricity bill [3]. Furthermore the energy efficiency will be increased due to the fact that the energy is consumed closer to the generation and therefore smaller distribution lines are required, and lower overall transmission/distribution losses.
The main challenges with a local energy market are that it shall be lucrative for the different participants, otherwise the participants will sell and buy energy somewhere else. To achieve a lucrative market the market has to be equitable for the different participants. Furthermore a challenge with a local energy market are to have a intelligent structure in the market model that enables good forecast in production and demand for the participants and submits reasonable bids.
The possibilities from local energy markets make it a hot topic to research and are still in the early stage and demonstrations of real-world applications are required [1]. This thesis is done in collaboration with an on-going EU-funded project - Fossil Free Energy District (FED), where Chalmers is one of the partners. Therefore there is a strong initiative to design and model a local energy market model at Chalmers, to evaluate how operating a local energy market would benefit the University as well as the other actors in the energy market. The internal electricity grid at Chalmers is a good starting point to develop to a local energy market due to the fact that they have some local electricity production units. Earlier studies on Chalmers grid have been made [5], which investigates the possibilities of the grid as a micro grid, where the technical and economic benefits are evaluated. This study [5] will be used as a foundation of the simulation and data collection.

1.2 Goal

A local energy market would enable distributed energy production to be better utilized. The aim of the thesis is therefore to propose a design of a local energy market and implement the design in an General Algebraic Modeling System(GAMS). To verify the market model a case study using data of Chalmers campus will be carried out. This will not only verify the logic in the model works but it will also demonstrate the use and benefits of a local energy market. The focus will be on the electricity market, but there will be some interactions with the heating system.

1.3 Objectives

In order to achieve the goals above the thesis has the following specific objectives which are to:

- Design a local market framework for energy trading.
- Develop of a computational model for market trading.
- Perform a case study using the developed model with data from the Chalmers campus.

1.3.1 Design a Local Market Framework for Energy Trading

In order to have an efficient local energy market there have to be clear rules for the market participants [6]. Market participants should not have market power enabling them to manipulate the prices to create greater revenue for them self. The market should also handle the Distributed Energy (DE) production well. Since PV and small scale consumption are hard to forecast the market should be able to handle the trade efficiently without costly balancing settlements [7]. Therefore, the first objective of the thesis is to design a local energy market. Therefore in order to make market as efficient as possible, the following criteria must be considered and answered.

- Define the local energy market and flexibility market.
- Communication / measurement system.
- How to submit bids
- How the bids are cleared and price settlements.
- Time frames for bids and dispatch intervals.
- Degree of competition.
- Information about the bids.
- Responsibility for flexibility.
- Responsibility for ancillary services and deviations.
- Responsibility for the energy market.

1.3.2 Develop of a Computational Model for Market Trading

To be able to test the local energy market model it will be simulated in GAMS (General Algebraic Modelling System) which is a high-level modelling system for mathematical programming and optimization [8]. The modelling will follow this procedure:

- Model every market participant.
- Model the local energy market.
- Integrate the model of market participants with the local energy market model.

1.3.3 Perform a Case Study Using the Developed Model with Data from the Chalmers Campus

After the market is modelled, the data from the Chalmers campus will be used to test the local energy market model. The data is for four weeks, one week in January, one week in April, one week in June and one week in October. The results will show the efficiency of the local energy market, what financial and energy gain there might be if LEM is employed. A discussion about the local energy market and its impact.

1.4 Scope

This project will only focus on the market in a Swedish context and use available data from the internal grid at campus Chalmers Johanneberg. The local market will be simulated from this data and different building on the campus area will be the simulated as different players in this local market. Only electricity will be modelled but there will be some interaction with the heating in the buildings. Market aiding tools such as forecast models will not be designed but implemented from other well established models. The technical aspects of the local grid such as voltage, frequency etc. will not be modelled but only the trading of energy and services making up the market.

1.5 Thesis Outline

The thesis consists of six chapters including the introduction. The chapters are summarized below:

- Chapter 2 provides a technical background to the project, the theory needed to the project, some previous works in local energy market and energy market background.
- Chapter 3 explains how the project was performed and conducted.
- Chapter 4 presents the most interesting results for the different type of scenarios and analyses the results and discussion about the results.
- Chapter 5 presents conclusions for the thesis and some proposals of future work.

2

Technical background

This chapter describes the most essential parts for an energy market, the underlying theory and different components to establish an energy market. The chapter also contains previous local energy market studies.

2.1 Distributed Energy Resources

In the following section, different technologies that can be used in local energy market to produce energy are briefly described for the reader. These technologies have in common that they are easy to scale up and can be suitable for a smaller energy market.

2.1.1 Solar PV

Solar photovoltaic (Solar PV), or solar cells, converts solar energy directly into electricity. Solar cells are made of layers of semiconductor material, when sunlight is absorbed by the semiconductor, the energy from the sun knocks electrons loose from their atoms and lets the electron flow through the material to produce electricity [9]. Solar cells are possible to be mounted on rooftops and on facade on buildings and easy to scale up by just adding more cells. If there is battery storage the electricity can directly be stored in the battery, otherwise the electricity goes through an inverter and out on the AC grid.

2.1.2 Combined Heat and Power

Combined heat and power (CHP) is a plant that produces both heat and electricity. A CHP plant produces electricity by the utilization of a stream or gas turbine with high temperature or pressure. The heat is extracted in the form of hot water through heat exchangers.

2.1.3 Ramping

When modeling thermal plants in an energy system it is important to consider the technical constraints regarding ramping, commitment, startup etc. [34]. This will also affect other units regarding flexibility such as batteries and demand response.
Power plant flexibility is crucial to manage variability in loads and provide grid support service. The most common type of measure flexibility is ramp rate, which is the rate a certain power plant can increase or decrease their output and the ramp rate unit is [power/time]. The ramp rate are depending on the operating conditions, unit capacity and technology.

2.1.4 Wind Power

Wind power uses the kinetic energy in airflow to produce electricity through turbines [10]. Wind power can have high fluctuations on a short time scale, but are consistent during longer time periods. They produce no greenhouse gas emission during operation and uses little land, however they have a high noise level and not appealing in city environment, and are therefore not placed in the central part of cities.

2.1.5 Heat Pump

The majority of heat pumps in mass use are used in heating individual houses. The power of such heat pumps ranges from single up to dozen of kilowatts. There are four types of heat pumps: air-to-air, water source, absorption heat pump and geothermal. The most common is the air-to-air [14], also a large proportion of these pumps are used as heating the facility during the winter and as air-conditioning appliances during the summer. The basic task of a heat pump, transfer of heat from the low-temperature heat source to the high-temperature heat source, this can be accomplished in various ways. Heat pumps are attractive options for controllable load, these are: The power consumption of the load is large enough to compensate power fluctuation by control of its power consumption and the loss of convenience by control of power consumption is minor [15], both these requirements are fulfilled with heat pumps.

2.1.6 Energy Storage

Energy storage units are used as energy buffer or backup to counteract power imbalances between the supply and demand sides. Energy storage systems consist of a wide array of different technologies, some of these different technologies are described in the following section.

2.1.6.1 Batteries

Batteries are available in different size, capacity range and electrochemical form. Most used electrochemical form are, Nickel-iron, Nickel-Cadmium, Nickel-Metal Hydride, Lead-acid and Lithium Ion batteries. Lead-acid batteries are the most mature and cheapest energy storage device, but the disadvantage with this technology is the limited cycling capability [11]. Lithium Ion batteries have the highest energy density among the four types mentioned, but they are also the most expensive [3] but are the most suitable for storing high power [12].

2.1.6.2 Electric Vehicles

As the amount of electric vehicles increases the possibilities to vehicle-to-grid power. The concept of vehicle-to-grid is that electric vehicles provide power to the grid while the vehicles are parked. This concept are most suitable for quick response and high-value electric services [13] to balance fluctuations in load.

2.1.6.3 Flywheel Energy Storage

Flywheel energy storage (FES) uses electric energy as input and stores it in the form of kinetic energy. The kinetic energy is the motion of a rotor, when short-term backup power is required the inertia allows the rotor to continue spinning and the resulting kinetic energy is converted back to electricity, new FES can have efficiencies up to 80% [44]. FES are commonly used in hospitals and in data centers due to the fact of their short response time and capability of delivering high power levels. FES have low maintenance and long life cycles but have high standby losses.

2.1.7 Demand Response

Dynamic energy management is an approach to managing load at the demand-side [37]. Permanent demand reductions, and regulating the demand from peak hours to off-peaks hours can lower the total energy cost. This regulation can be accomplished through sophisticated measuring systems and advanced communication systems. Examples of this type of demand response are, lightning that turns off completely in unused areas or lowering the ventilation efficiency for a short time during peak-hours.

2.1.8 Microgrid

A microgrid is in this thesis considered as a low voltage network with distributed controllable generation, energy storage and load demand that can be operated both islanded and connected to the grid [40]. The local energy market is the transactions of energy, services and money within the microgrid. The local energy market operates both with the microgrid and the wholesale market.

2.2 Theory

In this section optimal power flow, stationary battery storage and the solar panel theory are presented.

2.2.1 Power Flow Equations

Optimal power flow (OPF) is a numerical analysis for adjusting the power flows in a power network to achieve optimal value of a predefined objective, such as production costs or losses [19]. OPF is a more realistic formulation than economic dispatch function due to the fact that OPF accounts for the physical nature of power system including network security constraints. OPF problems often seeks to find an optimal profile of active and reactive generations to minimize the total operating costs of an electric power system with consideration to network security constraints. The problem is formulated on the basis of Kirchhoff's laws in terms of active and reactive power injections and voltages at each node in the system.

Objective function:

$$J = \sum_{i=1}^{NG} C_i P_i \tag{2.1}$$

A common objective function used in OPF studies is the minimization of generating costs and can be expressed as Equation (2.1). NG is the set of all generating units including the generator on the slack bus. C_i is the cost function of the generator.
The network equations are obtained from Kirchhoff's Laws governing the power flow and nodal power balances as follows Equation (2.2)-(2.3):

$$P_i - PD_i = \sum_j |V_i||V_j|Y_{i,j}cos(\theta_{i,j} + \delta_j - \delta i) \tag{2.2}$$

$$\text{for } \forall \quad i = 1, ..., N; i \notin Slack$$

$$Q_i - QD_i = -\sum_j |V_i||V_j|Y_{i,j}sin(\theta_{i,j} + \delta_j - \delta i) \tag{2.3}$$

$$\text{for } \forall \quad i = 1, ..., NL$$

V is the bus voltage magnitude, δ is the voltage angle associated with V, $Y_{i,j}$ is the element of bus admittance matrix, θ is the angle associated with $Y_{i,j}$, P and Q are real and reactive power generation respectively, PD and QD are real and reactive power demand respectively and NL is the number of $P-Q$ buses.
Generation and Voltage Constraints:
The generation constraints sets the limit for the grid power, during operation no constraints from the grid power. Equation (2.4) and (2.8) indicate this.

$$P_{grid}(i,h) \leq \infty \tag{2.4}$$

$$Q_{grid}(i,h) \leq \infty \tag{2.5}$$

$$V_{min}(i) \leq V(i) \leq V(i)_{max} \tag{2.6}$$

where $V_{min}(i)$ is 0.95 and $V_{max}(i)$ 1.05.

$$0 \leq P_{pv}(i,h) \leq \ P_{pv_installed} \tag{2.7}$$

where $P_{pv_installed}$ is the maximum installed solar PV capacity.

$$0 \leq P_{CHP}(i,h) \leq \ P_{CHPmax} \tag{2.8}$$

where P_{CHPmax} is 600 kW.

2.2.2 Stationary Battery Storage

The energy storage systems (ESS) are used as energy buffers or backup.
To maintain and establish how much energy that is stored in the batteries the State of Charge (SOC) must be monitored, SOC is expressed as seen in Equation (2.9).

$$SOC(i,h) = \frac{E(i,h)}{E_{rated}(i)} \tag{2.9}$$

Where E is the total energy stored in the battery and E_{rated} is the total installed battery capacity. The SOC is limited between 0 and 1, as seen in Equation 2.10

$$0 \leq SOC(i,h) \leq 1 \tag{2.10}$$

The change in SOC is expressed in 2.11 :

$$SOC(i,h) = SOC(i,h-1) + \frac{\eta_{chr} \cdot P_{chr}(i,h-1)}{E_{rated}(i)} - \frac{\eta_{dis} \cdot P_{dis}(i,h-1)}{E_{rated}(i)} \tag{2.11}$$

Constraints regarding the charging and discharging for the batteries are stated in 2.12

$$P_{chr} \cdot \eta_{b,loss} \leq P_{dis} \tag{2.12}$$

Where $\eta_{b,loss}$ is the combined losses from the ESS containing both η_{chr} and $\eta_{transmission}$

The η_{chr} and η_{dis} are assumed to be fixed on all the ESS. η_{dis} is set to 0.95 according to [22] and η_{chr} is set to 1.

2.2.3 Solar Panel

Due to the lack of data available from Chalmers Campus solar PV and the total solar irradiance is instead used to estimate the power output from the solar PV. The irradiance data is taken from Swedish Radiation Safety Authority [21] and from Chalmers location in Johanneberg. An irradiance profile is used for every hour of the day for the whole year of 2016. The power output from the solar PV is estimated using Equation (2.13) where DNI_{STC} is the irradiance used for standard test conditions to calculate the rated power of solar cells, which is $1000W/m^2$ according to IEC 60904-3 [20]. P_{rated} is the rated output from the installed solar PV. The DNI data is collected from the Swedish Radiation Safety Authority [21].

$$P_{pv}(h) = \frac{DNI(h)}{DNI_{STC}} \cdot P_{rated} \tag{2.13}$$

2.3 Market

In the following section the keystone for a working energy market is described.

2.3.1 Market Clearing Price and Settlement Systems

There are different ways of ending an auction and this will have different effects on the price and competition of the market. To have an as efficient market as possible it is necessary that the participants don't have market power to influence the outcome of the price in the auction [36] [29]. In an ideal competitive market where the participants are price takers, which means they do not have the power to influence the auction clearing price by having different bidding strategies. The participants bid their true valuation. In an ideal market everyone also has the same information, there are sufficient number of buyers and sellers and the commodity is indistinguishable [29]. The price of this ideal competitive market will then be settled at the price equilibrium where the buyer and seller meet in supply and demand as in basic economics [43]. The auction can either be cleared at a uniform price or at pay-as-bid price. In the uniform clearing everyone pays, and gets payed, the price of the last cleared auction. Figure 2.1 illustrate this concept . In a pay-as-bid price every participants pays, and gets paid, for the price they matched their bid with [29].
Auctions in energy is done daily, the information about quantity and prices are often public and the degree of uncertainty in demand is relatively low. These are the main factors why the power auctions are so influenced by tactics from the participants [29]. Some argue that uniform pricing will cause the market to be more expensive than when Paid-as-bid since all transactions will be at the highest level. However, if the market participants do not bid their marginal price in a Pay-as-bid market, the bids will be higher than the marginal price causing the costs to increase. If using uniform prices the participants bidding below the clearing price will be rewarded the difference between their bid and the clearing price as a profit which will be an incentive to bid the marginal price. This is one argument for using uniform prices [29]. There are only studies showing that Pay-as-bid will increase the total costs and none that shows, as argued by some, that it will decrease [29]. This is as mentioned due to the fact that participants will start guessing the clearing prices and bid higher than the most efficient market.
Uniform markets however are also subjected to strategies from the bidders to maximize their profit. Participants can still raise their bids as long as they are being called in the auction. This is something that participants with multiple production units can do. Raising the bid of one they think will be the marginal will generate a lot of profit for the rest of the production units, pushing the prices upwards. Participants with many plants below the marginal price has more incentive to raise the bid with a marginal plant in order to get more profit.
The authors in [29] also highlights that the Pay-as-bid market might cause more expensive plants run while cheap plants are idle just because they guess the clearing price better. This will make the market inefficient. Pay-as-bid can also give an unfair payback to participants. If a participant is unaware of the marginal prices it might be payed less than the actual value of the energy. To avoid this from happening participants bid higher than they actually need to, causing the prices to rise. To be payed less than the actual market value in an auction is called winner's curse [29].
Both uniform pricing and pay-as-bid can cause price inflation in price. It is important to make sure that participants do not have market power to influence the prices causing the market to be inefficient. Information among the participants, number of

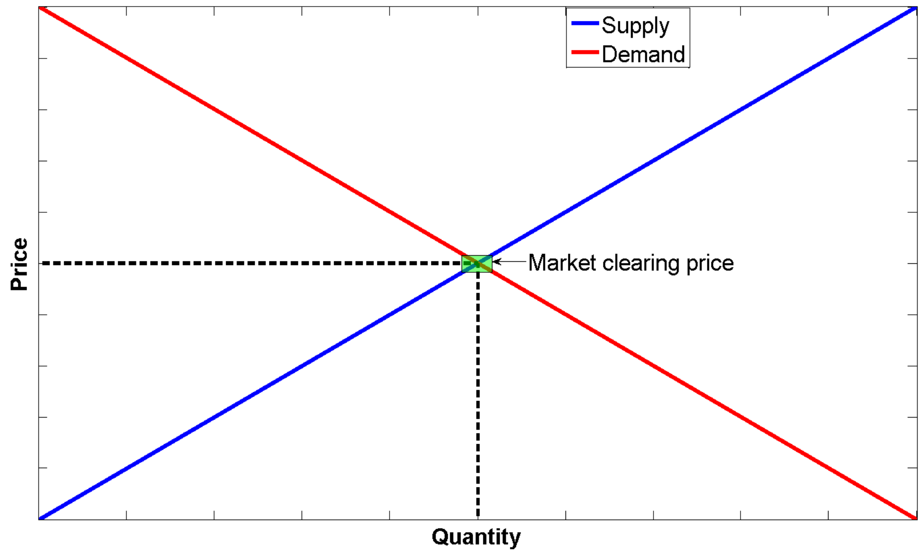

Figure 2.1: Market clearing price

participants and is key in doing so.

2.3.2 Merit Order

The different energy producers have different marginal costs. Units that are producing in a market are often illustrated by a merit order curve. When sorting the producers in merit order, all producers are ranked by their marginal cost. The cheapest to the left and then they are sorted in increasing order, see Figure (2.2). The width of the unit is the power it can supply. The demand curve can then be integrated in the merit order curve to illustrate what will be the cost for electricity. Integration of renewable energy (RE) pushes the merit order to the right since RE has a very low running cost [34] [35] .

2.3.3 Ancillary Services and Balancing Groups

In order to have a functioning grid there has to be ancillary services. [33] Developed a model that simulated seven ancillary services that they considered to be the main ones: losses, regulation, spinning reserve, supplemental reserve, load following, energy imbalance, and voltage support. In the same report they also cited The Federal Energy Regulatory Commission's, an agency in the United States, definition for ancillary services as the following:

> *"The Federal Energy Regulatory Commission (FERC 1995) defined ancillary services as those services necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system." [33]*

Different generators can provide different types of ancillary services, different customers require different types of ancillary services and ancillary services can differ dra-

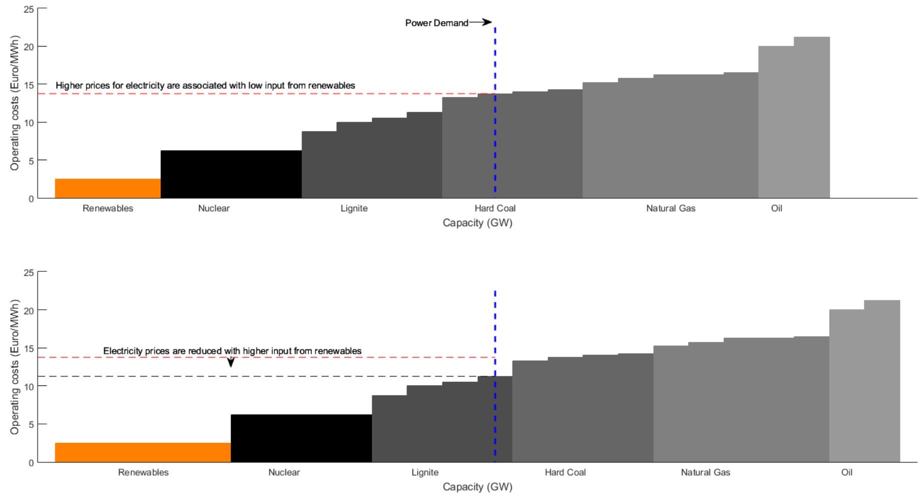

Figure 2.2: Typical merit order with renewables,pricing only for scale

matically over time [33]. Therefore it can be rather difficult to integrate the ancillary services in a market. The responsibility for the ancillary services needs to be defined and the cost for them needs to be defined. There can be auction markets for ancillary services, bilateral contracts or the participants can be self-provided [29]. Different ancillary services can also have different markets. It is however ultimately the system operator who is responsible for the grid stability.

The market for ancillary services can be exploited by distributed energy production to get a better energy system [31]. By not only contributing to the energy market but also to the ancillary service market the efficiency of the system can increase. There has been suggestions on how an architect of microgrids should be constructed and how the market for ancillary services and energy should be managed [31]. The ancillary service reserve energy can become increasingly important with intermittent distributed energy production [32]. The report suggest a market where households and small business can submit bids to the balancing responsibility groups. If a participant wins the auction it needs to reserve their allocated capacity. This will make the balancing groups more independent, reduce market power and reduce losses in the grid.

2.3.4 Auction and Bilateral Markets

Trades between the seller and buyers are arranged in two different ways, in a centralized market the seller sells their electricity to an intermediary which sells it further to the end customer. The second is known as a bilateral trade, a bilateral market is where the seller and buyer negotiate a contract between them and doesn't participate on the auction market [29]. Bilateral markets have different prices of every transaction whereas in pool markets, all participants usually pays the same price for the energy. Bilateral markets are more common in forward markets where the trading period is in one week up to several years. In the short time horizon however, the opportunity cost of finding a bilateral contracts increases and pool markets are more common.

2.3.5 Time Frames

The time frame of the auction is also important to consider. The time frames considered are both what time interval the energy will be delivered and for when the auction will start and end. A market can either have fixed time frames considering all bids before clearing and starting a new auction. A continuously cleared market also have time frames for the trading but the bids are cleared as soon as they have a matching bid [30].

The time for the market has been studied for hour and day ahead and there are proposals for how this should be done. These markets however require good forecast which can be difficult to do in mini grids for renewable energy and few number of consumers. To not trade according to the forecast is costly since there are penalties for balancing settlements. The motivation to implement a market with a short trading horizon is to eliminate the forecast errors and also to have a balancing mechanism in the market together with the trading mechanism[30]. Real time markets are used to balance the energy system [29]. These markets are usually operated by an Independent System Operator (ISO) who is responsible for the balance in the system. For electricity to be delivered from one point to another in the grid there must be a market for balancing the electricity flow. The real time market is often an adjustment market from what was forecasted by the participants. Deviations from the forecast is payed for in the real time market to maintain system stability.

To correct for imbalances firstly Automatic Generation Controls (AGC) are used. This is generators that correct their speed depending on a frequency meter. To ensure the system can handle unexpected changes in load or generation there are also reserves. Operating reserves can respond in some seconds up to 30 minutes and replacement reserves can respond in 60 minutes[29]. There is also a category called reliability-must-run (RMR) that is scheduled in advance and is ensuring the voltage level at critical points in the grid [29].

The fundamentals of a real time market is for the system to be able to cover its imbalances. There are differences in how this is done through different market models.

2.3.6 Communication and Measurement Systems

Measurement systems in energy market is a vital part for the different participants. For the consumer smart meter is the most appealing, a smart meter is often called smart to imply that it includes significant data processing and storage [27]. Smart meter enables two-way communication with the meter, and often uses two different types of wireless networks HAN (home area network) and WAN (wide area network) [28]. The potential in smart meters exceeds the scope of this thesis, but the two main advantages are described.

A smart meter allows remote and immediate reading of electricity consumption, enables more accurate and intra-day billing and handling of unpaid bills [26]. Smart meter data can help determine more precise forecasting with help from more accurate electricity consumption [26] and enable the integration of local generation of energy [26]. Smart meters are also available for producers and power station with similar system as for the consumer.

2.3.7 Billing System

The electricity contract are divided into two different segments. The first is the actual consumption of electricity that is used during the time period (usually a month), measured from an electric meter for the residence or business. The second is from the grid operator for delivering the electricity from the grid into the residence or business.

2.3.8 Auction Types

Auction types are divided into four different types:
The first-price sealed-bid auction. The bidders submit their bids simultaneous, each bid are sealed and unknown for the other participants, and the highest bid wins the auction [30].

The second-price sealed-bid auction, also called Vickrey auctions. The bidding procedure are the same as the first-price sealed-bid auctions accept for that the highest winning bid pays the value of the second-highest bid [30].
The ascending-bid auction, also known as English auction and is the most common type for auctions [31]. Different participant openly bids against each other in real time, where each new bid is ascending than the previous. The auction ends when no participants are willing to bid anymore.
The descending-bid auction, also known as Dutch auction (due to widely used in sale of flowers in The Netherlands). In this auction type the seller gradually lowers the price from a high initial value until some bidders accept the current price and accepts it [30]. This auction form is also an interactive auction.
All of these four auction types can be more or less complex in their structure but are described in their simplest form. Auctions can be doubled-sided as well as one-sided. One-sided auction is when only generators submit sealed-bid offers, double-sided auction is when suppliers and different load-serving entities submit bids [24].

2.3.9 Locational Marginal Price and Area Pricing

A grid is not always able to transport all energy to a certain location. This phenomenon is called congestion. The marginal cost is different for different producers. If the cheapest one is not able to transport everything through the grid, another more expensive producer have to produce that energy and transport it another way than through the congested point in the grid. Due to this congestion in the grid the consumers will have different price for electricity depending on where they are located in the grid. To be located close to the cheapest producers or at a point of the grid with little problems with congestion often means that you have lower energy price. The customers in the grid will have different energy prices depending on where they are located. If all customers have the same price it means that there are no congestion problems in the grid or that all production units has the same marginal price. The system operator can charge the customers differently for every point in the grid. This is called Locational Marginal Price .
Another option to deal with the congestion problem is to have Area Pricing. This means that the TSO will divide the customers into different areas and every area will have an

area price for electricity. Different areas will have different prices for the same reason as Locational Marginal Price. There will not be any differences of price within the area.

2.3.10 Energy Only and Simultaneous Market

The nature of the electricity system causes it to have a real time market. Without a real time market the operation of the system would collapse since the forecasts are more or less never accurate. The electricity system also has markets before delivery, often day ahead. However, the electricity market needs a market for reserves, energy and ancillary services. The focus is often on the energy market but the dynamic between the three is important to consider. The organization of the three can be done in multiple ways. One way to organize the markets is to first clear the energy market, then the reserve and the ancillary service market. Another way is to run the markets simultaneously [42].

2.4 Previous Work

This section discusses some previous work on the subject of Local energy market, as well as experimental tested local energy markets in different areas in the world.

2.4.1 An auction design for local reserve energy markets

In [41] the beneficials in a decentralized generation in a local reserve energy market with an appropriate auction design. The reserve energy market is a complex market and the auction mechanism needs to be as simple and easily understandable as possible to attract as many participants as possible.
For the electricity grid it is crucial that there is exactly the same amount of power input as consumption, if this requirement is not fulfilled, blackouts or disorders will appear. Therefore the reserve energy market for balancing purpose is vital. In the current market it is hard for smaller prosumers to participate in the central energy market due to high thresholds of power input. The sellers are market participants that bid at the auction, these sellers are typically smaller residential home or business with solar panels, micro-CHP plants or storage batteries. The buyer of reserve energy is the local balance group. Through an online auction platform different private households and small business that dispose of decentralized generation units can submit bids to cover its reserve energy needs. In [41] the auction takes place weekly for the following week for each hour of the day.
Each bid is composed of a price [$/kW]and the amount of capacity to be reserved q [kW], each bid are denoted from an individual bid, these bids are then ranked from the lowest to the highest. Each bidder knows his cost as a function of quantity c(q). The buyer will not buy energy from the local market if the cost is significantly higher than in the global market. According to article 29 (3) of the European Council Directive 90/512/EEC sets the price difference up to 3 % giving preference to local offers. If there is not enough reserve energy offered or the price exceed those on the global market the buyer should be able to register its needs with the TSO and the successful bidders are informed about the quantities that they are obliged to reserve.

In [41] two different bidders strategy cases is established. In the asymmetric case, each bidder tries to maximize their expected profit (profit are the sum of all bids less the respective cost), in the cost the technology-related costs (like fuel) are not included.The different bidders have equipment in various sizes in the range from 3 kW to 50 kW which is randomly distributed .To prevent gaming and market power they ensure equal chances for each participant in the calling process, the paper uses a uniform distribution with a probability factor that their bid is successful. In the symmetric case, all bidders have identical q (this could happen when all bidders have the same generation).

For the simulation in the asymmetric market an analytic solution is hard to determine therefore a learning strategy is established and transformed into an algorithm.

In [41] three main scenarios are scrutinized, varying in the information provided to the bidders. In these three scenarios each bidder's bid may or may not be accepted, if the bid is not accepted the bidder will adapt his strategy as long he will generate a profit.

The results from [41]simulations concludes that the more information for the bidder's is provided the fiercer the competition becomes. Also notable from [41] is that considerable profits can attract more participants in the market and lower cost for the balancing group. Further research can be made in how actual human bidders react to the proposed design.

The paper [41] have the same bidding possibilities as in this paper where the different agents can submit their bids through an bidding platform. However in [41] they tested different bidding strategies more carefully.

2.4.2 Aggregator Trading and Demand Dispatch Under Price and Load Uncertainty

In [46] the author presents an aggregator decision support model for demand scheduling, including demand response and purchase bid optimization for day-ahead markets. Furthermore income from providing electricity to consumer and costs related to imbalances, rescheduling and energy not delivered are also included in the model. The aim of the of the model is to provide decision support when defining purchase bids to the market. The model includes several parameters such as, demand dispatch and demand response, technical potentials for demand response, uncertainties in price and loads and an economic risk mitigation measure. Aggregators in [46] are viewed as service providers linking the individual consumers with the power market.

The model is based upon some market conditions such as, The planning is performed under uncertainty where prices and loads can be regarded as stochastic, the considered actor is a balance responsible party and that the actor is the price taker. The developed mode focus on two market places for physical trading of electricity, the spot market and the balance settlement. The developed model is based on stochastic optimization, where a set of scenarios represents all the stochastic parameters in the developed model. The scenarios includes for instance, wholesale day-ahead spot prices, unadjusted load levels representing the aggregated load profile of the aggregator consumer portfolio, imbalance prices paid by balance responsible actors for deviations.

All these scenarios are expressed as linear and are therefor easy to solve with well established methods. The objective of the scheduling problem is to maximize the total revenue over the considered time horizon.

To ensure the feasibility with the developed model a case study using historical data from Nordpool for spot prices and imbalance prices was used. The simulated trading on the spot market is assumed to be performed 24 hours ahead consumption. The aggregators load in the case study are assumed to represent a percentage of the national load. The consumer price is set to a low value compared to the market prices and the compensation level for not being able to serve the customers with energy is set to high in comparison to other energy prices.

The results from the case study indicates that the revenue from an aggregator is relatively small and that the economical benefit from executing demand response is limited. However with an increase in more renewable energy sources such as wind and solar power may make it more lucrative in the future.

In [46] the 24 hours ahead market have some similarities to this project where the revenues from the aggregator is relatively small but an increase in renewable energy sources will make it more lucrative.

2.4.3 Experimental Local Energy Markets

Different testings of local energy markets have been conducted in different areas over the world.

2.4.3.1 EMPOWER

The EMPOWER market concept has been tested in Hvaler in Norway and is in the early pilot stage for sites in Germany and Malta. The EMPOWER project have identified different value boosters to make the local energy market more attractive for the users and attract more prosumers and producers. These incentives are for example consumer membership, smart capitalization on flexibility and different add-on services. The market model is based on web based shopping clubs and platform based business models supported by smart phone apps or web browser. Producers or consumers that wishes to become a member of the local trading community will sign up in ways that are typical for shopping clubs, similar to that of AirBnB. By signing up with the community the user will yield benefits such as discounts on services and products offered through the community, for example that all members trade for free. To control large fluctuations in surplus or large deficit that causes congestions or overload on the infrastructure, Demand-response and use of storage is needed. This operation have Demand-response requires installation of controllers and the local DSO could benefit from the local market with orchestrated flexibility. To enhance trade and increase the trade volume on the market the local sellers are given a price mark-up and local buyers gets discount if they buy locally produced energy, this is done by including the taxes and tariffs in the spot price and gives a lower price for the buyer and the taxes and tariffs for the seller are covered entirely by the market. The EMPOWER market in Hvaler in Norway have attracted suppliers of wind generators, batteries, PV panels and controllers for DR and more prosumers are willing to join the market. However since this market is still in is early stage it's too early that any conclusions can be made.

2.4.3.2 The Nobel Project

The Nobel project started in December of 2012 and ended September 2014. The project was located in Alginet, a village located in the province of Alicante in Spain. The goal of the project was to facilitate and manage the electricity trading between the citizens of a smart city [16]. A smartphone app and a website were developed for the 5000 participants to sell and buy their energy [17] [13]. The market design is based on the stock exchange model with discrete fixed-sized time slots throughout the day [16].
The market architecture for the Nobel project is as followed: A market participant submits an order, with following information, price limits, order configuration and timeslot. If an order misses out on some of this information, the order is returned to the participant with information about what's missing. Since an order might not match, the participant can update it or cancel it during a certain timeslot. If there is a matching order between selling and buying, the trade is executed and the market output manager is notified[1].The matching process is repeated every time an order is inserted or updated, and follows the First-Come, First-Served policy. On average energy savings were around 12% for the citizens and up to 58% for large consumers [17].
Further work on this project are proposed by [17] is to have fully automated trading agent strategies based on security, risk and privacy issues on the market. Also agent with different types of objective functions needs to be investigated.

3
Method

In the following chapter the methodology of the thesis is presented. It describes how the work was carried out, what data and assumptions was used, how the market model was constructed and how the computational model was constructed.

3.1 Methodology

The work was carried out by firstly conducting a literature study. The literature review is presented in 2.4 and included for instance theory about local energy markets, market modelling, real-time demand response, multi-agent systems and energy markets. The literature review was the foundation of the market model design. The design was developed by analyzing the different options in designing a LEM and how this theory could implemented in a way that satisfied the purpose of the thesis. The different design options was discussed and trade offs for pros and cons with the different options was considered resulting in the proposed design. The proposed market design was then be implemented in an optimization program. In this thesis the optimization program used was GAMS. A general model for the market players was developed and used. By varying the data used in the model every market player could be simulated in the same optimization model. The optimization was supported by matlab and excel in order to provide the right data to the optimization model and in order to conduct multiple simulations of the market. After the market model was designed and implemented in the computational model it was then simulated to investigate how the market players and the market itself behaves in different scenarios. The resulting data is then discussed in order to highlight how realistic the model is and what shortcomings it might have.

3.2 Data and Assumptions

In order to test the market model data from Chalmers Campus was used. Firstly, the grid was simulated using the data from the Chalmers. Secondly the demand from every market player was taken from historical data from the buildings at the campus. Thirdly the energy resources such as PV and batteries was taken from the Chalmers campus. The market was tested with three different scenarios about energy equipment. The first scenario was the current installations and the other two with different investment scenarios.

3.2.1 Chalmers Grid

The Chalmers grid that is used in parts of the market model is acquired from previous studies of the chalmers grid [45]. The market use OPF to determine how the energy market should be balanced close to delivery. This is explained in section 3.3.3. In order to conduct the OPF the grid data is used together with equations of how the losses and voltages in the grid behaves. The OPF model used in GAMS is taken from the same thesis as the data about the grid but with adjustments in the constraints in order to make the optimization fit the market model. The branch data from the grid are shown in Table 3.1 and the transformer data are shown in table 3.2. An illustrative figure of the grid is presented in Figure 3.1

Table 3.1: Branch Data

Bus-connection	Line Length[m]	R [mΩ]	X [mΩ]	Line-Charging [μF]	Current-Limits [A]
1-3	75	9.4	6.4	0.030	385
1-5	70	8.8	5.9	0.028	385
5-6	40	7.0	3.4	0.014	300
5-12	275	34.4	23.3	0.11	385
5-41	250	14.4	6.4	0.0245	385
8-17	110	13.8	9.3	0.0440	385
10-41	100	20.6	9.3	0.035	300
12-13	25	1.6	1.1	0.005	770
12-16	15	1.9	1.3	0.006	385
12-17	20	2.5	1.7	0.008	385
12-18	25	3.1	2.1	0.010	385
13-14	420	52.5	35.6	0.168	385
16-19	25	3.1	2.1	0.010	385
17-31	330	41.3	28.0	0.132	385
17-33	80	10.0	6.8	0.032	385
18-23	225	28.1	19.1	0.090	385
18-35	400	50.0	33.9	0.16	385
23-25	300	37.5	25.4	0.12	385
25-27	165	20.6	14	0.066	385
29-35	400	51.3	34.8	0.164	385
35-38	10	1.3	0.9	0.004	385
38-39	25	4.0	1.2	0.004	205

3.2.2 Consumption

The data used for the consumption is taken from real data from the campus during 2016. The model is simulated during four periods, one week for every season. This is done because the loads vary over the year and the production of the solar PV for one week in January, one week in April, one week in July and one week in October.

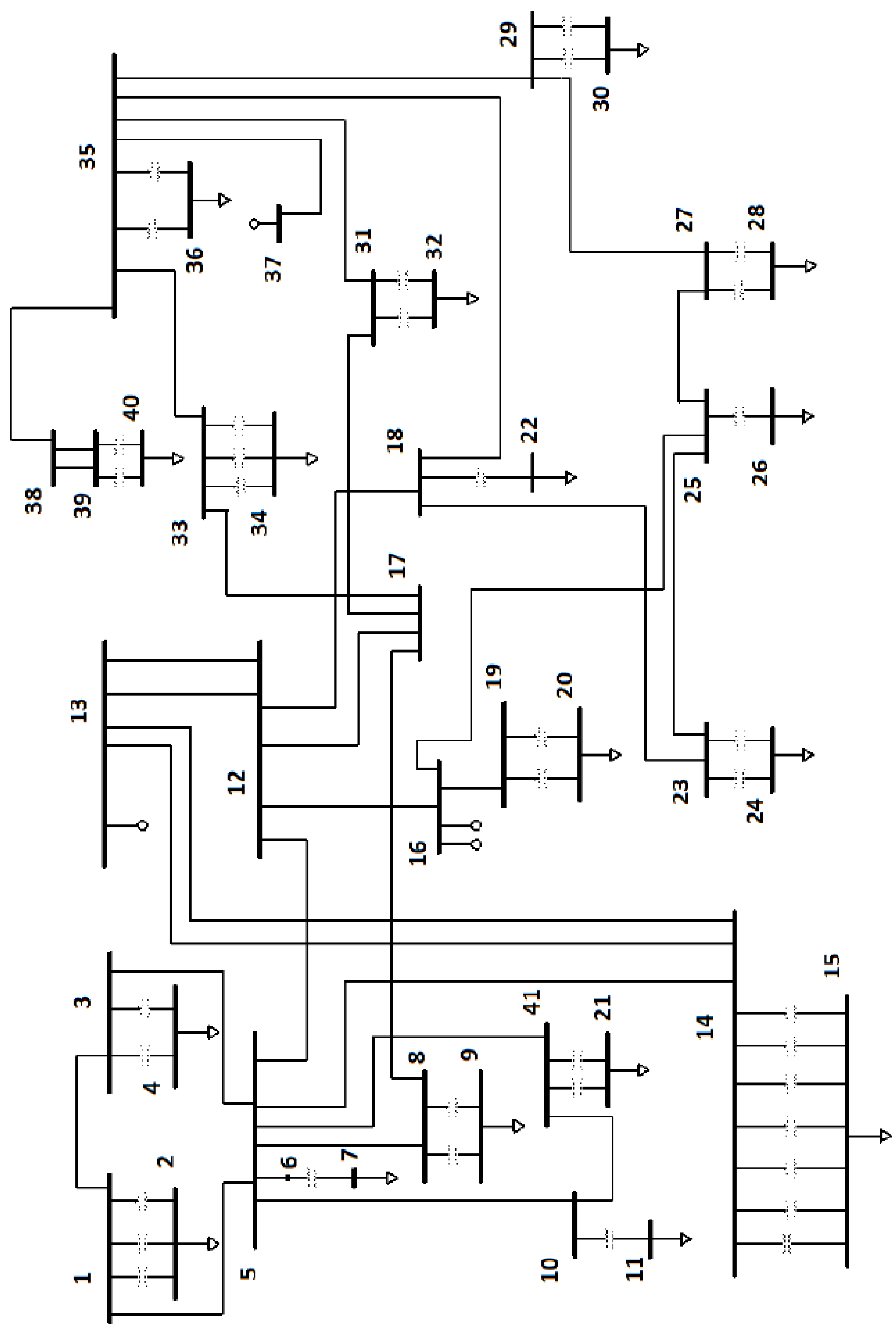

Figure 3.1: Illustration of the Chalmers grid

Table 3.2: Transformer Data

Bus-connection	X[%])	Rating [kVA]
1-2	4.8	800
1-2	5.0	800
1-2	5.2	800
3-4	5.69	800
6-7	5.8	1000
8-9	5.8	800
10-11	4.82	800
14-15	5.0	1250
14-15	5.0	1250
14-15	4.9	1250
18-22	5.5	1250
19-20	6.31	800
19-20	5.0	800
21-41	5.7	800
21-41	6.3	1000
23-24	4.27	400
25-26	4.8	800
27-28	4.9	800
29-30	5.8	800
31-32	4.5	1250
33-34	6.3	800
33-34	6.3	800
35-36	5.2	800
35-36	4.9	600
39-40	5.2	1250
39-40	5.2	1250

3.2.3 Investment in Energy Equipment

This refers to how the market will behave with an increased amount of energy equipment in the local energy market. This includes an increase in solar PV, Batteries and the possibility to use Demand Response. The simulations with an increase in energy equipment will be performed in two stages. One case based on an investment that could be done in a near future and that is not very extensive. The second scenario is when the investments have been made even more extensively than that. In table 3.3 the different cases are shown with the total capacity of the LEM illustrated in each cell.

Table 3.3: Investment Scenarios

Scenario	CHP Capacity [kW]	Solar PV Capacity [kW]	Battery Capacity [kWh]	Demand Response Capacity [kW]
Base Case	600	110	-	-
Scenario 1	600	510	200	10% of total demand
Scenario 2	600	1000	600	10% of total demand

3.2.4 Prices

The energy and reserve market operating 24 hours before delivery is optimized to maximize social benefit and the prosumers are optimized to maximize their profit. All of these three optimizations are thereby optimized based on the different prices that are used in the model and therefore they are significant in how the market operates. Because of this significance in the model the prices and the relation between the prices will be investigated. The bidding price for energy on the LEM is based on the Nordpool spot price and the same goes for the reserve energy that is being activated. The reason for choosing to have prices based on the NP prices is to have prices close to the actual cost of electricity and also to have have a realistic fluctuation. The other reason is the fact that it is difficult to motivate why someone would sell energy on a market that pays less than another market where you would get paid more. The benefit from the LEM is not necessarily the energy price but the savings in ancillary and grid services. This is why the prices are based on the NP prices. In order to have every agent bid differently on the market all agents multiply the NP price with a factor that is shown in table 3.4

Table 3.4: Price factor

	Lower limit	Upper limit
Price case 1	0.9	1.1
Price case 2	0.8	1.2

$$Pri(i,h) = NP(h)_{spotprice} \cdot U([LowerLimit],[UpperLimit]) \tag{3.1}$$

$$Pry(i,h) = NP(h)_{Reserveprice} \cdot U([LowerLimit],[UpperLimit]) \tag{3.2}$$

Where U is a random variable uniformely distributed between the upper and lower limit for each price case.
The prosumer forecast the prices and base their optimizations on this. Every prosumer has a price and is unlikely to be the same as someone else. Therefore the different prosumers might optimize and bid differently depending on what they forecast. The same principle is done for the reserve energy market.
Another variable in the price forecast that has significance is the variable K. This is as mentioned in 3.4 a probability factor for how much of the reserve energy that will actually be utilized. This factor can range between 0 and 1 but is in all simulations set to 1. This will maximize the profit from reserve energy in the forecast. The value 1 also correspond to the extreme case when the error is 15% for both the demand and supply, causing it to be able to be 30% units. This is the same value as the demand of reserve in the market 3.14. The factor of the most reserve that will ever be needed, excluding losses, and the demand for reserve energy will be 1 according to equation

$$K = \frac{ForecastError}{AvailableReserve} \tag{3.3}$$

3.2.5 Real Time Trading and Forecast Error

The market will also be tested in how the forecast errors affect it. The intra day trading depend on how much the forecast error is. In the model the forecast error is based on the forecast. The forecast is multiplied with a factor to get the forecast error according to equation 3.4 and 3.5 where U is a random variable uniformly distributed between the limits in the bracket. The factors are presented in table 3.5

Table 3.5: Forecast error

	Supply Factor	Demand Factor
Forecast Error Case 1	0.95	1.05
Forecast Error Case 2	0.85	1.15

$$Demand(i,h) = Demand_{forecasted} \cdot U([1, DemandFactor]) \tag{3.4}$$

$$Supply(i,h) = Supply_{forecasted} \cdot U([SupplyFactor, 1]) \tag{3.5}$$

Each agent will get a different forecast error every iteration and the intra day market has to solve this unbalance.

3.3 Market Model

The purpose of the market is to make use of the energy investments in the local grid as efficiently as possible. The market is supposed to be fair for all participants and all participants should also have a clear understanding of how the market works. The local grid is supported by the district, regional and national grid and have the possibility to import and export energy to ensure that the energy demand and production is met.

The market that was designed consists of three parts. The three parts together makes it possible to trade energy and also to handle uncertainties such as unforeseen consumption or lack of committed production. A timeline of the market operations are illustrated in figure 3.3. The two first parts, named Energy 24h and Reserve 24h, are operated 24 hours before delivery and are illustrated in figure 3.3 by the yellow area between hour 24 and 25 and referenced as 'Auction for 24 hours ahead'. The third part of the LEM is illustrated by the red part and is called real time market. The two markets operating 24 hours in advance are trading energy and reserves while the real time market makes decisions on who should trade the reserves based on OPF. It can be seen as the two first parts prepare the LEM for supplying energy and the third part executes it and ensures that enough energy is produced to meed the demands. The first part trades both energy and reserve energy and the third part ensures that the energy demands are met by supplying the energy and possibly the reserve energy as well.

The two auctions occurring 24 hours in advance are illustrated in figure 3.2. Firstly the market players make a forecast of what they believe their demand and production will be as well as what they believe the price for energy and reserve energy will be. They then make bids on the markets based on what will maximize their own profit. When this is done the energy market considers all bids and clears the market at a uniform price. The energy bids that were not cleared in the model is balanced with nordpool in order to satisfy all participants demands. This is done in the model in order to make the model run smoothly and to ensure that no agent is without their required power. Secondly the reserve energy market is cleared. The demand of the reserve market is based on what the demand will be multiplied by a factor. The whole market needs a certain amount of reserve and this is decided by the market operator. If the market players are not able to supply the required amount the model consider the grid to provide the rest. After the markets are cleared the agents will have commitments of what they need to supply certain hours. This is illustrated in figure 3.3 as the blue bar between hour 1 and 24. The agents then place their bids on the next hour knowing their limitations based on what they have committed to do the previous hours.

The third part of the market is the real time market. This is when the commitments come close to delivery and the market players need to stand up to what they have committed. Every agent will update their forecast for demand and production and if needed, they will inform the market operator that they can not commit to what have been agreed on the energy market. When this is done the market operator complies all the forecast errors. The market operator then consider all the options for reserve energy and based on the supply and demand for this reserve energy, as well as the OPF in the grid, the market operator makes a decision on who should supply and how much they should supply in order to minimize the transmission losses and thereby making the market as efficient as possible. This is called the real time market and the flow of information in this market is illustrated in figure 3.5.

3.3.1 Energy 24h

The energy market operating 24 hours before delivery is as mentioned where the $marketplayers$ in the LEM settles on how much they will trade among each other and at what price. The market is a uniform price market and does not consider physical location in the

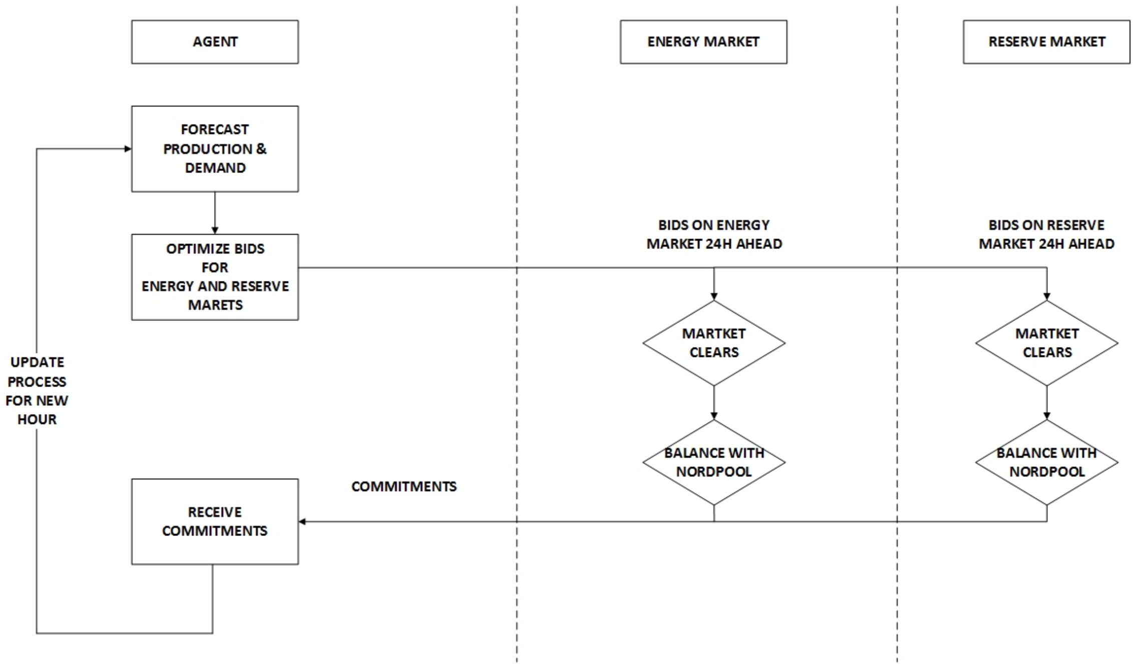

Figure 3.2: Interaction between the agents and the energy and reserve market operating 24 hours ahead

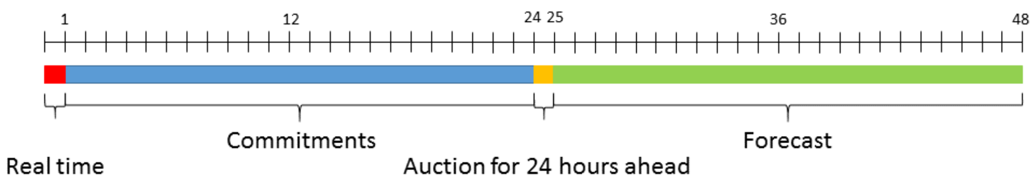

Figure 3.3: Time line of the local energy market

auction. The bids submitted are sealed for all participants to encourage a market with low gaming.

Objective function: The objective of the market is to maximize the social benefit for the market which is done by maximizing equation 3.6.

$$benefit = \sum_{j=1}^{n} (DB(j) \cdot S_{bid}(j)) - \sum_{j=1}^{n} (P_{sun}(j) \cdot S_{sun}(j) \\ + P_{bat}(j) \cdot S_{bat}(j) + S_{chp}(j) \cdot (W1(j) \cdot P_{min}(j)) + P_{chp}(j))) \tag{3.6}$$

Where j is the agent, n is the number of agents, DB is the energy demand bid in kWh, S_{bid} is the price in sek/kWh that the agent bids for energy, S_{sun} is the price bid for sun in sek/kWh, P_{sun} is the amount of sun energy that the agent bids in kWh. The same goes for CHP and battery where S is the price and P is the amount of energy. W1 and Pmin are special constraint for the CHP. Since the CHP can not produce less than a certain minimum, because of constraints on the furnace, the CHP has to bid at least the minimum when it is operating. W1 is a binary number for when the CHP is either operating or not.

Energy balance: The market has a energy balance constraint to ensure that the supply bids are met with the demand bids and this is expressed in equation 3.7.

$$\sum_{j=1}^{n} W1(j) \cdot P_{min}(j) + P_{chp}(j) + P_{bat}(j) + P_{sun}(j) = \sum_{j=1}^{n} P_b(j) \tag{3.7}$$

Where P_b is the cleared amount of energy that is being bought by the market players. This has the constraint that the cleared amount must be less or equal than the amount that is being bidded as expressed in Equation (3.8)

$$P_b(j) \leq DB(j) \tag{3.8}$$

As mentioned above the CHP has a constraint for how much it needs to produce to be able to operate. If the output is less than this the CHP can not operate and therefore the binary variable W1 is used. The constraint is expressed in Equation (3.9).

$$P_{chp}(j) \leq W1(j) \cdot P_{chp,const}(j) - P_{min}(j) \tag{3.9}$$

Where $P_{min}(j)$ is the minimum amount of energy that the CHP can have as an output and still operate. Because of this the actual amount produced by the CHP is expressed in Equation3.10.

$$P_{CHP,real}(j) = W1(j) \cdot P_{min}(j)) + P_{chp}(j) \tag{3.10}$$

The market optimization returns a value for how much every agent j have committed to either sell or buy at the hour when the auction is performed. Since the bids are known for every agent the market clearing price is set to the last bid that was cleared in the optimization. The indata for the market clearing is the minimum amount of energy that needs to be produced by the CHP in order for it to operate, the demand for every agent, the price every agent bids for buying energy, the bids for selling energy and the amount of energy to sell on the market. The solver used is MIP (mixed integer

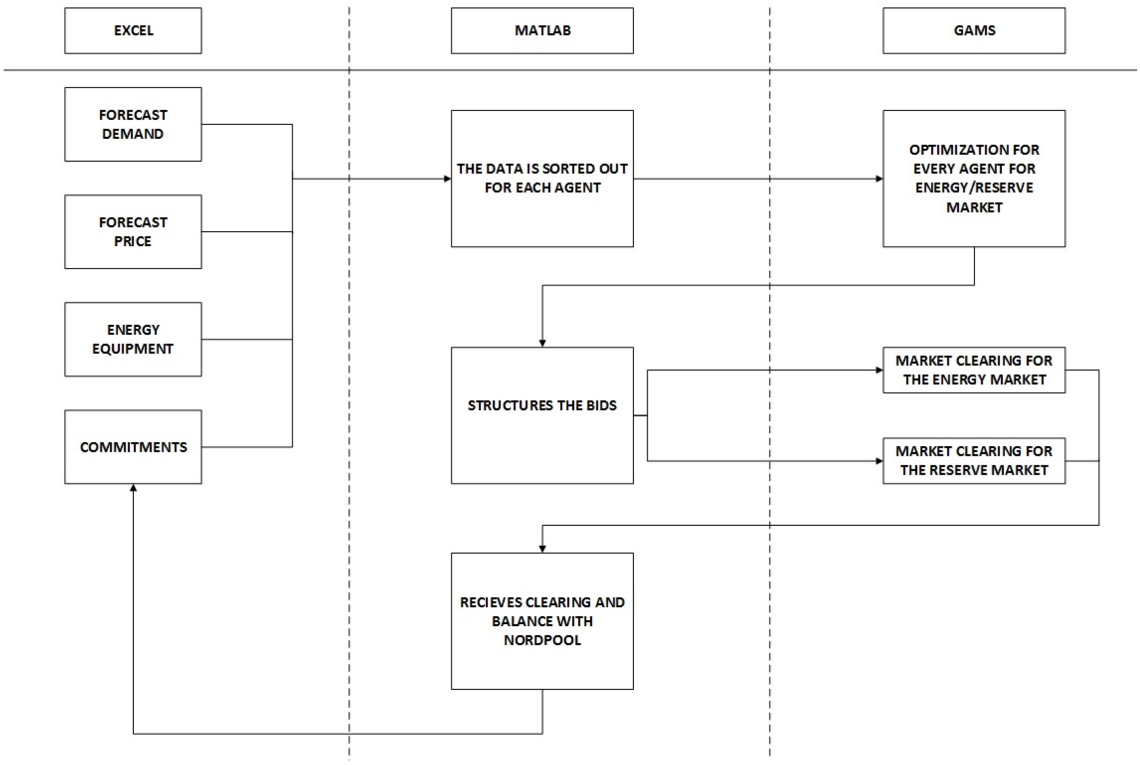

Figure 3.4: Illustration of how the data flows in the market model

programming) and the model itself is a linear model. The amount of energy traded on the energy market rarely balance itself perfectly and therefore the model exports or imports the amount that is not balanced in the LEM as illustrated in figure 3.2. In figure 3.4 the data flow of the market is illustrated.

3.3.2 Service 24h

Since the forecast for every agent rarely will be exact upon delivery the market is designed to have reserve energy that can be taken in to operation when needed. The service market is similar to the energy market in the sense that it receives bids from the agents. The bids contain how much reserve energy the agent is able to provide.
Objective function: The objective for the reserve market is the same as on the energy market, to maximize the social benefit. The optimization is done by maximizing the BenefitS in Equation (3.11).

$$\begin{aligned} BenefitS = \sum_{j=1}^{n}(DB_s(j)\cdot S_{bids}(j)) - \sum_{j=1}^{n} &+P_{bats}(j)\cdot S_{bats}(j) \\ &+S_{chps}(j)\cdot P_{chps}(j)+P_{resps}(j)\cdot S_{resps} \end{aligned} \tag{3.11}$$

Where DB_s is the demand bid for reserve energy in kWh, S_{bids} is the demand bid in sek/kWh. The S_{bats} is the price bid from the battery to be reserve, S_{chps} is the price bid from the chp to be reserve, S_{resps} is the price bid for the demand response to be reserve. If the market is not able to resolve the reserve energy necessary it use the overlaying grid and NP to do so.

Constraints: The balance Equation (3.12) works as a constraint to ensure that the right amount of reserve is bought.

$$\sum_{j=1}^{n}(P_{respons}(j) + P_{chps}(j) + P_{bats}(j)) = \sum_{j=1}^{n} P_{bs}(j) \tag{3.12}$$

Where $P_{respons}$ is the amount of energy that an agent offers in demand response. The demand response is assumed to be the ability to turn off the ventilation for one hour but with the constraint that the ventilation must be operating for two hours straight before and after this occurs. The ventilation is assumed to be 20% of every building. P_{chps} is the amount of reserve energy the CHP is bidding and P_{bats} is the reserve energy the battery is bidding. P_{bs} is the amount of reserve energy the market clears. Because of this there is the constraint that the amount cleared can not be greater than the amount being bidded according to Equation (3.13).

$$P_{bs}(j) \leq DB_s(j) \tag{3.13}$$

The GAMS model requires the amount of reserve energy bid by every agent as well as the demand for reserve in the system. It also need the prices for every bid. The outcome is the cleared bids from the auction and the model is solved with a MIP solver. Because of the interaction with matlab the bid for reserve energy, DB_s, is set for every agent in advance of going in to the GAMS model according to equation 3.14. It is in matlab that also the reserve supplies are set. The demand for reserve energy is decided by how much energy demand there is on the market according to 3.14. The bid for supplying reserve are decided in the market player model as can be seen in Figure 3.4. The market clearing price is based on what the bid was for the last supplier to be cleared.

$$Demand_{Reserve}(i) = 0.3 \cdot Demand(i) \tag{3.14}$$

3.3.3 Real Time Dispatch

When the energy and service market are settled the market awaits until it is close to delivery. This is illustrated in figure 3.3. Just before it is time for the delivery of the energy, also known as the red part in this figure, the forecasts are updated and the market prepares for how the reserve should be operated. All agents in the market update their forecast and send their updated demand and supply to the market operator. This is done by multiplying the original forecast with a factor. In this thesis different forecast errors are investigated according to table 3.5. For example when the forecast error is case 2 the demand is multiplied with a random number between 1 and $1,15$ and the supply is multiplied with a random number between $0,85$ and 1.

The market then use OPF to decide which reserve energy that should be operated. Since all reserve energy agents have won the auction and are ready to provide reserve energy the decision in who should do so is done by the grid operator. The grid operator use OPF to settle this. The purpose is to provide the reserve energy as efficiently and fair as possible, therefore the grid operator optimize the OPF to minimize the losses in the grid and decides who should be operating based on that.

Objective function:The loss in the grid is formulated by Equation (3.15). The OPF optimization receives information about how much every bus will produce and receive. It also receive information about who is committed to the reserve market and optimizes this variable to minimize the losses.

$$Loss = \sum_{i=1}^{n} (P_{res}(i) + P_{prod}(i)) - \sum_{i=1}^{n} P_{load}(i) \tag{3.15}$$

Where i is the bus, P_{res} is the active reserve energy, P_{load} is the demand and P_{prod} is the production.
Constraints: The power flow equations are formulated as Equation (3.16) and Equation (3.17).

$$P_{res}(i) - P_{load}(i) + P_{prod} = \sum_{j=1}^{n} |V_i||V_j|(G_{i,j} \cdot cos\theta_{i,j} + B_{i,j} \cdot sin\theta_{i,j}) \tag{3.16}$$

$$Q_{res}(i) - Q_{load}(i) + Q_{prod} = \sum_{j=1}^{n} |V_i||V_j|(G_{i,j} \cdot sin\theta_{i,j} - B_{i,j} \cdot cos\theta_{i,j}) \tag{3.17}$$

Where G and B are the real and imaginary parts of the admittance between bus i and j, θ is the voltage angle difference between bus i and j, V_i and V_j are the voltages at bus i and j. The grid operator then inform the agents in who should be operating and how much they should deliver. The market model does not consider any shorter time spans than the 15 minutes the intra day market operates at.
The constraint for the voltage is set so that it can not drop or peak at any bus according to Equation (3.18)

$$V_{min} \leq |V| \leq V_{max} \tag{3.18}$$

$$-I_{lim}(i,j) \leq |I(i,j)| \leq I_{lim}(i,j) \tag{3.19}$$

The computational model for the real time dispatch market solves which reserve that should be used in order to minimize the losses in the grid. It requires data about the grid connections between the buses. It also requires data about the demand, production and available reserve in all buses. It then solves the model non linear problem using a NLP(non linear programming) solver and returns the optimal usage of the available reserves. The result is determine which reserves that should be used in order to deliver the required power while minimizing the losses in the system. Figure 3.5 illustrate how the real time dispatch market operates in the computational model. It starts of by receiving the commitments from the two markets operating 24 hours ahead. It then divide the data evenly in to 15 minutes periods and sends these in to the GAMS solver explained above to sort out how to balance the forecast errors. If the LEM is not able to provide enough reserves it imports it from the grid.

3.4 Market Player

A prosumer is a member of the LEM and can be both a producer and a consumer. The model for the prosumer is used for every agent with different conditions to simulate every market participant. The prosumer's purpose is to maximize its own profit in the

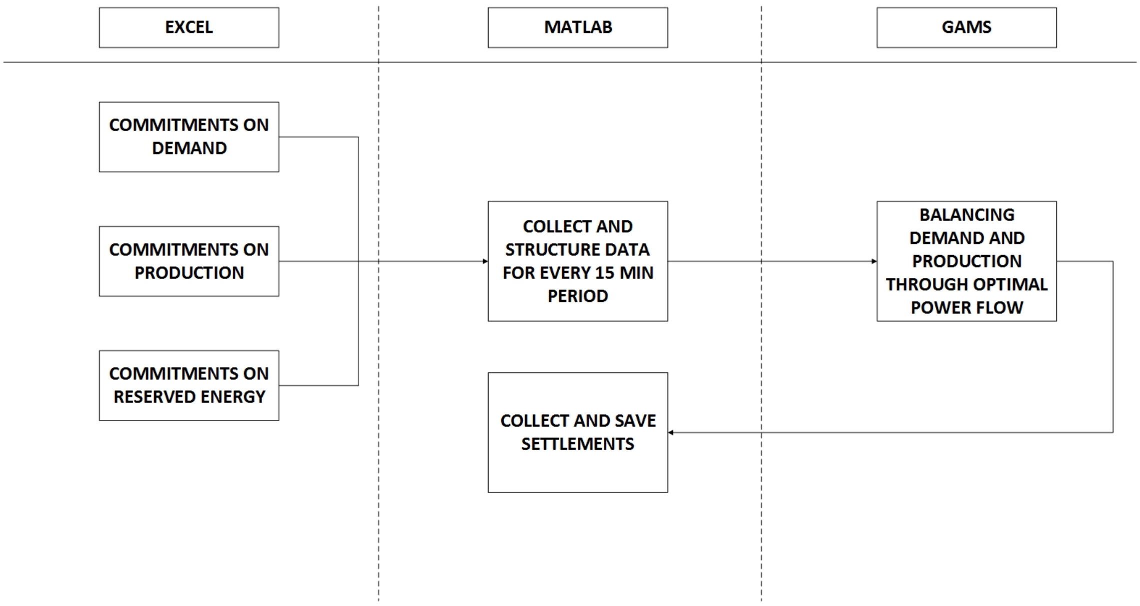

Figure 3.5: Data flow for the intra day market

market. This is done by forecasting demand, production and price of electricity in the market and optimize it's bidding according to that. The prosumer is the most intelligent part of the market simulation and is the one who decides how much to bid for and at what price.
Objective function: The purpose of the market player is to maximize it's own profit. The profit function for the market player is written in Equation (3.20).

$$Profit = \sum_{h=1}^{n} (IC_E(h) + CO_E(h) + IC_S(h) + CO_S(h)) - PPwr(h) \cdot GF) \tag{3.20}$$

Where h is hour, IC_E is the forecasted income from selling energy in the LEM, CO_E is the cost of selling energy in the LEM, IC_S is the income from selling reserve energy in the market and CO_S is the cost of selling reserve energy in the LEM and Pwr is the amount of energy imported and GF is the fee for using the grid. The fee in the simulations is 0.27 sek/kWh, the same as the fee for using the grid today[39].
The income from sold electricity is expressed in Equation (3.21).

$$IC_E(h) = Pri(h) \cdot Exp(h) + P_{heat}(h) \cdot S_{heat}(h) \tag{3.21}$$

Where Pri is the forecasted price for electricity and Exp is the amount exported to the market, P_{heat} is the amount of heat produced and S_{heat} is the price for sold heat. The heat price is set to four different values depending on what time of the year it is. The cost for selling energy is expressed as a function for producing it and is expressed in equation 3.22. Power from solar PV and batteries are assumed to have no production cost and therefore the function is only considering CHP.

$$CO_E(h) = CPEn(h) \cdot PEn(h) \tag{3.22}$$

Where $CPEn$ is the cost of producing one kWh of CHP and PEn is the amount of kWh produced. The profit and cost for being reserve is divided in to two parts. The first part is for standing reserve and the second part is for delivering reserve. In the model there is a parameter K that is the probability of the reserve to being used. A prosumer would therefor over a period deliver K and in turn get paid for delivering that and the prosumer would also not deliver 1-K and get paid for standing reserve. K is described more in 3.2.4. The equation for the profit from the reserve market is written in Equation (3.23).

$$\begin{aligned} IC_R(h) &= (PSe(h) + Pedy(h) + Presp(h)) \cdot PPSe(h) \cdot K(h) \\ &+ (PSe(h) + Pedy(h) + Presp) \cdot PryR(h) \cdot (1 - K(h)) \end{aligned} \tag{3.23}$$

Where PSe is the amount of CHP that is reserved, $Pedy$ is the battery energy that is reserved, $PPSe$ is the price for being active reserve, $Presp$ is the demand response that is being reserved and $PryR$ is the price for being reserve but not active. And the cost from the reserve market is epressed in Equation (3.24).

$$CO_r(h) = PSe(h) \cdot (CRSe(h)) \cdot ((1 - K(h)) + K(h) \cdot CPSe(h)) \tag{3.24}$$

Where $CPSe$ is the cost for the CHP to be standing reserve.
Constraints: The prosumer optimization has the possibility to have all the energy services that are considered $i.e.$ solar PV, CHP, battery, demand response and a demand for electricity. Every prosumer have pre-set characteristics that are loaded in to the optimization program for every agent. The constraints for the different energy services then determines how the agent will bid.
The battery has a constraint for how much energy it can contain in Equation (3.25), a constraint for how much it can charge and discharge every hour, and a constraint for how it's state of charge changes depending on that.
The physical constraints for the battery are described in Equation (3.26) where Emax is the maximum energy the battery can contain, Dis is the discharge rate from the battery for one hour and Chr is the charge rate to the battery for one hour.

$$\begin{aligned} Emax &= Battery_{max} \cdot Dis \leq Pemax \\ Emax &= Battery_{max} \cdot Chr \leq Pemax \end{aligned} \tag{3.25}$$

The battery also have a constraint for how much it can change it's state of charge. This is done by limiting the state of charge depending on the charging and discharging previous hour.

$$\forall h \neq 1 \qquad SOC(h) = SOC(h-1) + \frac{\eta \cdot Chr(h-1)}{Emax} - \frac{Dis(h-1)}{Emax} \tag{3.26}$$

For the first hour in the optimization the battery has a fixed state of charge

$$\forall h = 1 \qquad SOC(h) = SOCcom(h) \tag{3.27}$$

The discharging from the battery can be both to the energy market and the reserve market, therefor they are constrained to the total discharge capacity according to Equation (3.28).

$$Dis = Pedy + Pedi \tag{3.28}$$

The constraints for the CHP are written in Equation (3.29) - (3.32).

The energy produced by the CHP can not exceed the maximum production of the unit as expressed in Equation (3.29).

$$PEn(h) + PSe(h) \leq Max_{chp} \tag{3.29}$$

Since the reserve energy is not a definite producer it has to be within the flexibility limits of the CHP. Therefore it can not be greater than the ramp rate as in equation 3.30.

$$PSe(h) \leq Rup \tag{3.30}$$

The CHP can not ramp up faster than a certain limit, and for the first hour in the optimization it has to be within limits from what it have committed from previous hours.

$$\begin{aligned} \forall \quad h \neq 1 \qquad & PEn(h) - PEn(h-1) - PSe(h-1) \leq Rup(h) \\ \forall \quad h = 1 \qquad & PEn(h) \leq Rup(h) + CHPcom(h) - PSe(h) \end{aligned} \tag{3.31}$$

The same goes for ramping down with the CHP

$$\begin{aligned} \forall h \neq 1 \qquad & PEn(h-1) - PEn(h) \leq Rdown(h) \\ \forall h = 1 \qquad & PEn(h) \geq CHPcom(h) - Rdown(h) \end{aligned} \tag{3.32}$$

Sold heat

$$P_{heat}(h) = PEn(h) \cdot \alpha \tag{3.33}$$

Where P_{heat} is the amount of produced heat and α is the heat to power ratio of the CHP.
The CHP plant at Chalmers campus have a maximum capacity of 600 KW_{el}. The power-to-heat ratio are assumed to be constant and are set to 1.6 [38] .
Constraints for demand response

$$P_{resp}(h) \leq Vent_{max} \tag{3.34}$$

$$\begin{aligned} \forall h \qquad & P_{resp}(h) \cdot P_{resp}(h+1) = 0 \\ \forall h \qquad & P_{resp}(h) \cdot P_{resp}(h+2) = 0 \\ \forall h = 1,2 \qquad & P_{resp,com}(h) \cdot P_{resp}(h) = 0 \end{aligned} \tag{3.35}$$

The resulting export and import to the agent is then according to Equation (3.36).

$$Exp(h) = P_{chp}(h) + Pedi(h) + P_{PV}(h) - Chr(h) - Dem(h) \tag{3.36}$$

$$Imp(h) = -Exp(h) \tag{3.37}$$

The market player requires data for every agent every in order to make an optimization. Firstly it requires the demand forecast of the market player. This is as mentioned before based on historical data. It also needs the price forecast for that agent. This is also as mentioned before based on historical data. Other than that it requires information about what capacity it's energy equipment has. If the agent does not have a certain energy equipment this is set to zero. Lastly it requires the solar production forecast which is based on historical data from solar irradiation in Gothenburg. The data flow of the information is illustrated in figure 3.4 and as it can be seen the data is collected and sorted by matlab and GAMS only makes a optimization of one agent at the time for one hour. To ensure that the agent makes a good optimization the agent also receives data about it's commitments the 24 hours before the optimization is done. This data contains information about the SOC in the batteries and also the commitments of the CHP. By having the commitments the agent knows how much energy it has in the battery as well as how much it can ramp the CHP. From the market player's optimization expressed above the model will return the desired amount of energy it would like to import or export as well as what price it desires to do so. This information is the bids that are used in the energy and reserve market. Since the optimization for the market player is non-linear MINLP (mixed integer non linear programming) was used as solver.

4

Results and discussion

In this chapter the results from the computational model are presented. The results are also discussed and explained. The model was tested with three different investment scenarios and every scenario was tested with two different price scenarios and two different forecast error scenarios. The results of all simulations are presented and discussed but graphs are emphasizing on how the market behaved with 15% forecast error and 20% price difference since the effects were more noticeable in this case.

4.1 Agent behaviour

The amount of local energy production, consumption and storage of electrical energy are the main outputs of the local energy market. The consumption and production of the agents are, as described in the methodology, somewhat pre-determined through the forecast which is based on historical data from the campus. However, the built-in forecast error causes the results to be unpredictable within the forecast error limits. The price forecasts are also varied in the simulations which effects the tradings on the market. The resulting demand and production are presented in Section 4.1.1 and 4.1.2. The storage is operated based on the optimization's made by every agent and is presented in Section 4.1.3.

4.1.1 Demand

The demand for the different agents is based on historical data and the same data is used for all scenarios. Therefore, the demand is close to identical for all three scenarios. As mentioned there are some differences because of the forecast error that is used in the model, described in Section 3.3. The demand used in the model is presented in figure 4.1 where the different colours represent different agents. Only the demand used in scenario 2 is presented in the report since the demand is so similar during the different scenarios.

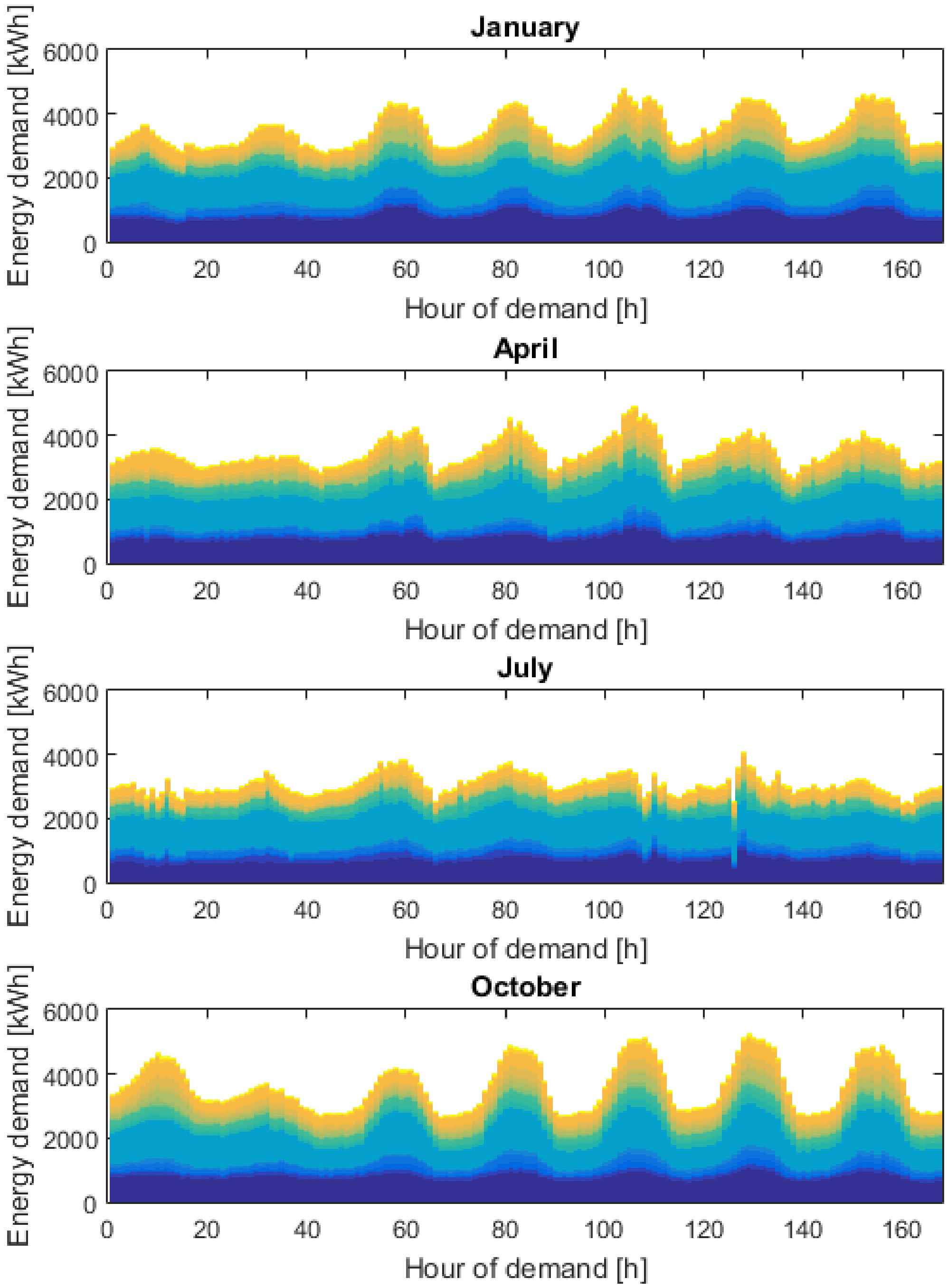

Figure 4.1: Demand during the different seasons. This demand is similar during all scenarios and every colour represent one agent

Table 4.1: Amount of electricity produced by the solar PV in the three different scenarios. All data is given in [kWh]

	Base Case	Scenario 1	Scenario 2
January*	787	3651	7160
April*	3955	18338	35957
July*	2299	10663	20908
October*	286	1329	2606
Average*	1832	8495	16657

*The results are for one week in the month

4.1.2 Production

The production differ during the different scenarios. This is mainly because of the increased solar capacity while the CHP capacity is held constant during the different scenarios. The production from the CHP is the same during all scenarios. In January it produces 600 [kW], in April and October it produce 350 [kW] and in July it does not operate. This is further discussed in Section 4.2. See Section 3.3 for more specific data about how much capacity that is installed during the different scenarios. Figure 4.2 illustrates how much power that is produced from solar PV during the different seasons. The solar PV production during the base case and scenario 2 are following the same pattern since the same data for solar irradiation is used. The only difference is the scale of the production. Table 4.1 illustrates the amount of electricity produced from the solar PV during the different seasons and scenarios.

It can be seen in Table 4.1, the solar production is following the same pattern for all scenarios. This is as mentioned because the same solar radiation data is used for all scenarios. The highest production from solar PV is in April in Scenario 2.

4.1.3 Storage

The storage capacity also increases with different scenarios as can be seen in Table 3.3. The SOC for different agents in scenario 2 are presented in Figure 4.3. As can be seen the batteries charge and discharge. This is done to minimize the agent's cost. The charging and discharging are somewhat similar when it comes to charging and discharging in all scenarios where there are batteries and therefore only one scenario is presented in the report. The differences are the capacity being charged and some minor differences might be because of the price difference in the forecasts. However these are small and all scenarios use the same historical data for prices.

The batteries charge and discharge within their limits and react to changes in their forecast prices. It can be seen in Table 4.2 that with more batteries (Scenario 2), the amount of reserve energy provided by the agents increases, which is due to batteries and the demand response possibility. The amount of energy traded with Nordpool also decrease with higher investments in energy equipment as can be seen in Table 4.4 and Table 4.3. This is because the solar PV production that makes the agents more self-sufficient and the batteries makes it possible for the agents to store over production for hours when the production is lower than the consumption.

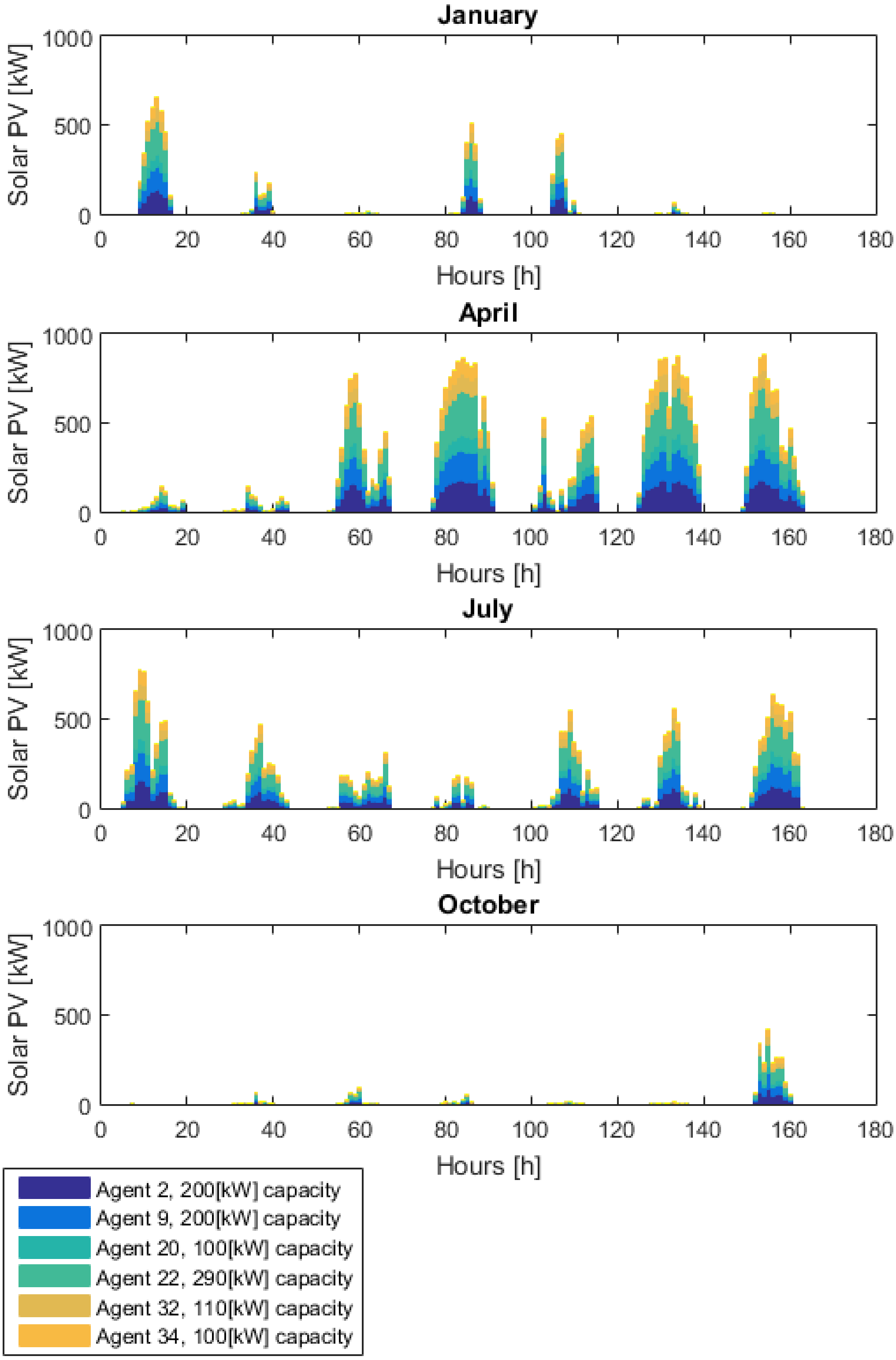

Figure 4.2: Solar production during the different seasons for scenario 2. Every colour is an agent

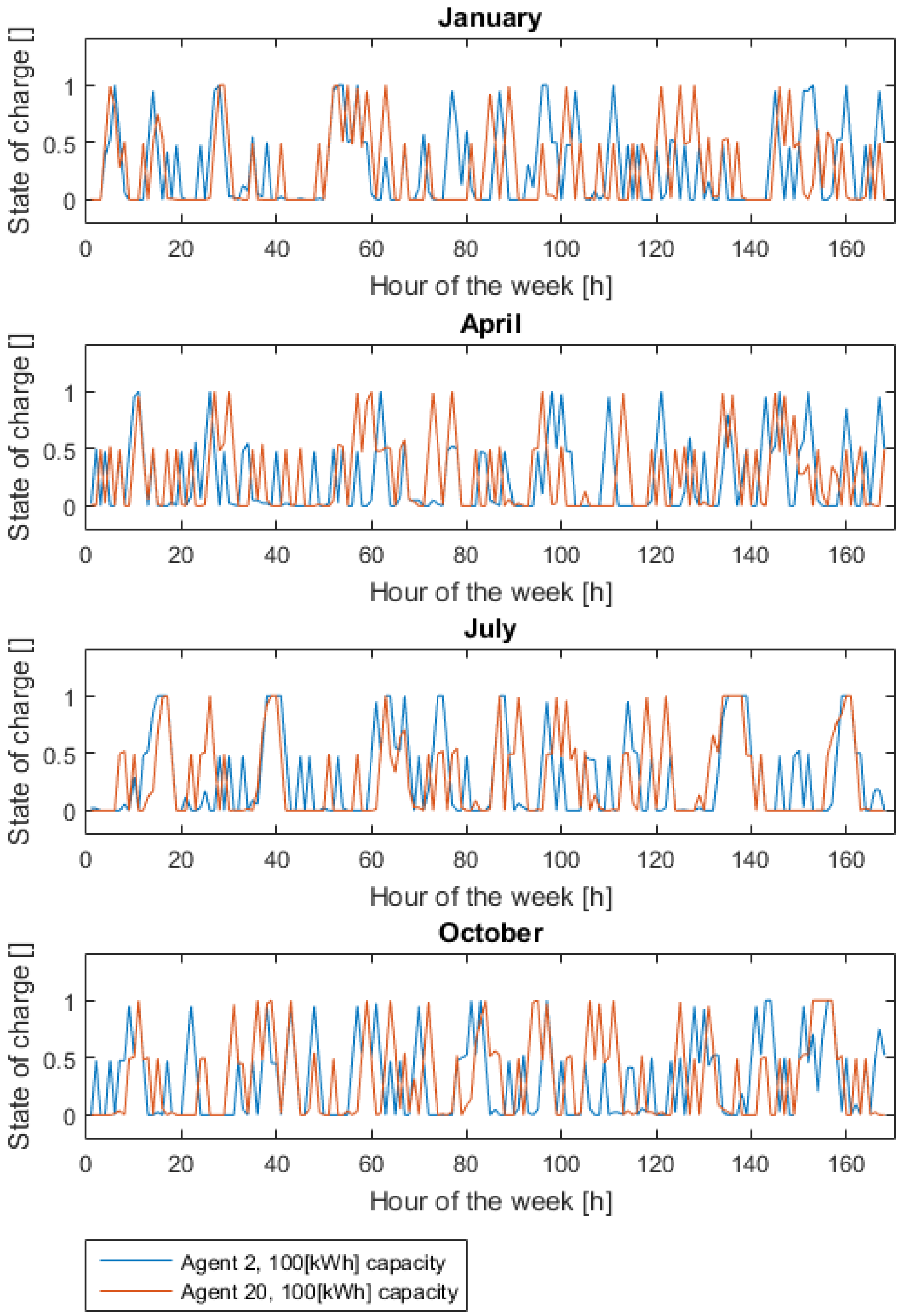

Figure 4.3: Battery state of charge during the different periods for scenario 2 with 20% price difference and 15% forecast error

Table 4.2: Percentage of reserve energy provided by the agents in the LEM. The remaining reserve energy is provided by the grid

	Base Case	Scenario 1	Scenario 2
January*	0	0,08	0,29
April*	0,79	0,85	0,93
July*	0	0,09	0,24
October*	0,73	0,82	0,89
Average	0,38	0,46	0,59

*The results are for one week in the month

4.2 24h Energy Market

The energy market trades differently during different seasons and different scenarios. The trading depends on the bids from the agents and thus on how the agents forecast. The three different scenarios have the same demand during the seasons, with minor differences caused by the forecast errors. The electricity production and the battery utilization are however different in the three scenarios and therefor the amount of energy traded will differ. The amount of electricity bought from the local energy market by every agent are presented in Figures 4.4 - 4.6. Every figure has four graphs representing one season of the year. The graphs are taken for when the price difference is 20%, a full compilation of all the scenarios and price differences are presented in Table 4.3 and Table 4.4. Notable from these figures is that the sold energy during July is almost zero in all the different scenarios, this is due to the CHP is not profitable during this month and is thus not operated.

Figure 4.4 illustrates the amount of energy bought on the LEM during the different seasons during the base case. The different colours represent different agents within the LEM. The same principle applies for scenario 1 and scenario 2 in figure 4.5 and figure 4.6 respectively. As can be seen in the graphs the amount of energy traded are highly dependent on what season of the year it is.

The energy demand that is not being provided by the trading within the LEM is provided from the grid. Figures 4.8 - 4.10 show how much energy it is being imported from the grid. Each colour represents an agent and it is noticeable how the import curve follows the demand curve in figure 4.1. This is logical when looking at the amount of energy traded on the local energy market which is held pretty much constant at either 600 [kWh] or 350 [kWh] depending on the season.

The market behaves differently, as one would expect, during the different scenarios and seasons. Noticeable is that limits the market tends to stop at. These are the same as the limits for the CHP production and it is in fact the energy from the CHP being traded a majority of the time. The CHP, which plays a significant part in the LEM, reacts to the price of district heating as can be seen in figure 4.4, 4.5, 4.6. By maximizing the profit, the CHP produce its maximum output of electricity and heat in January when the price for district heating is the highest. In April and October it is not as profitable to sell district heating and therefor it sells more on the reserve market. It is however still profitable to sell electricity and heat during April and October and therefor it still oper-

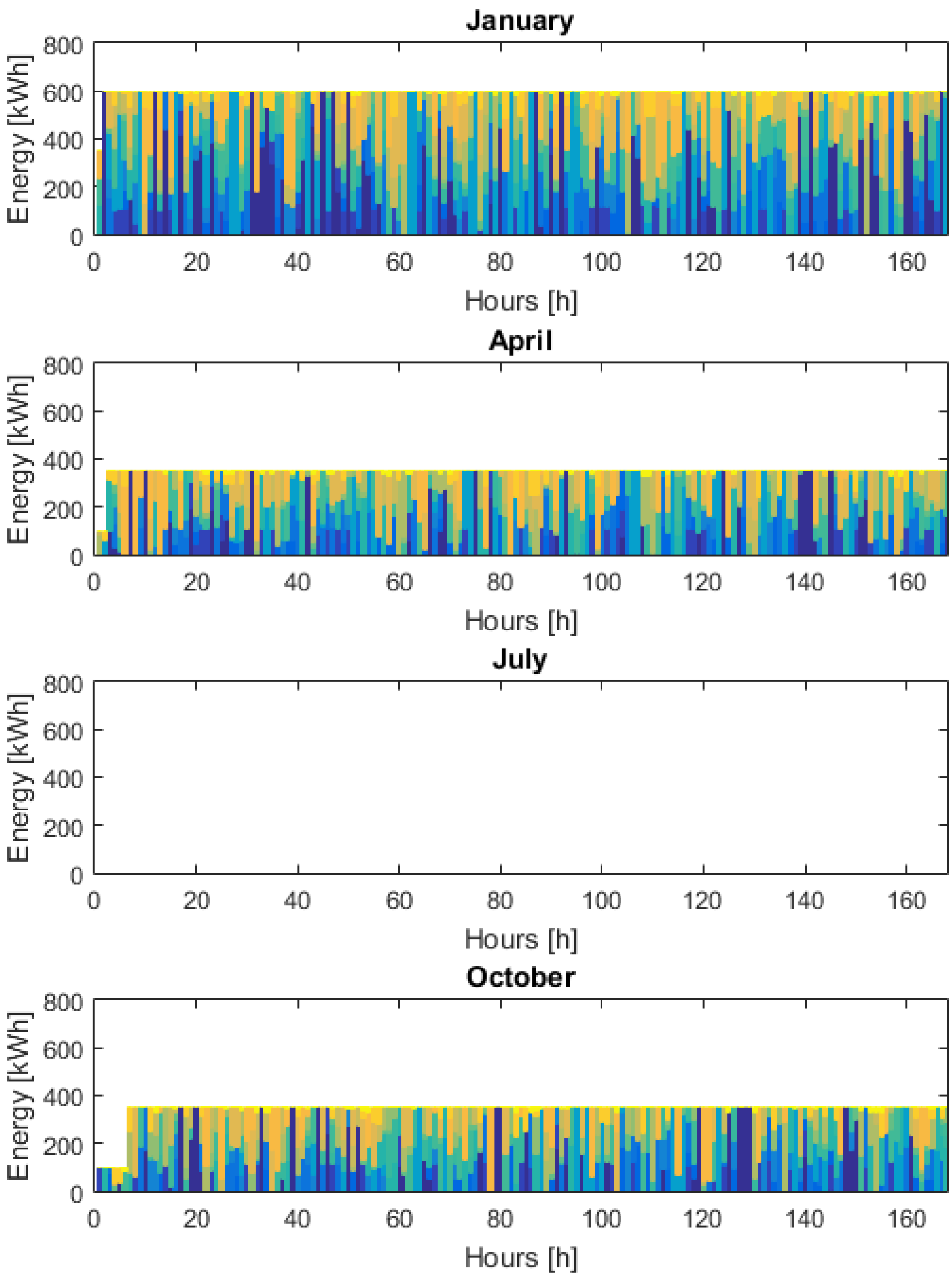

Figure 4.4: Energy bought on the LEM during the different seasons for the base case. Each colour represent an agent

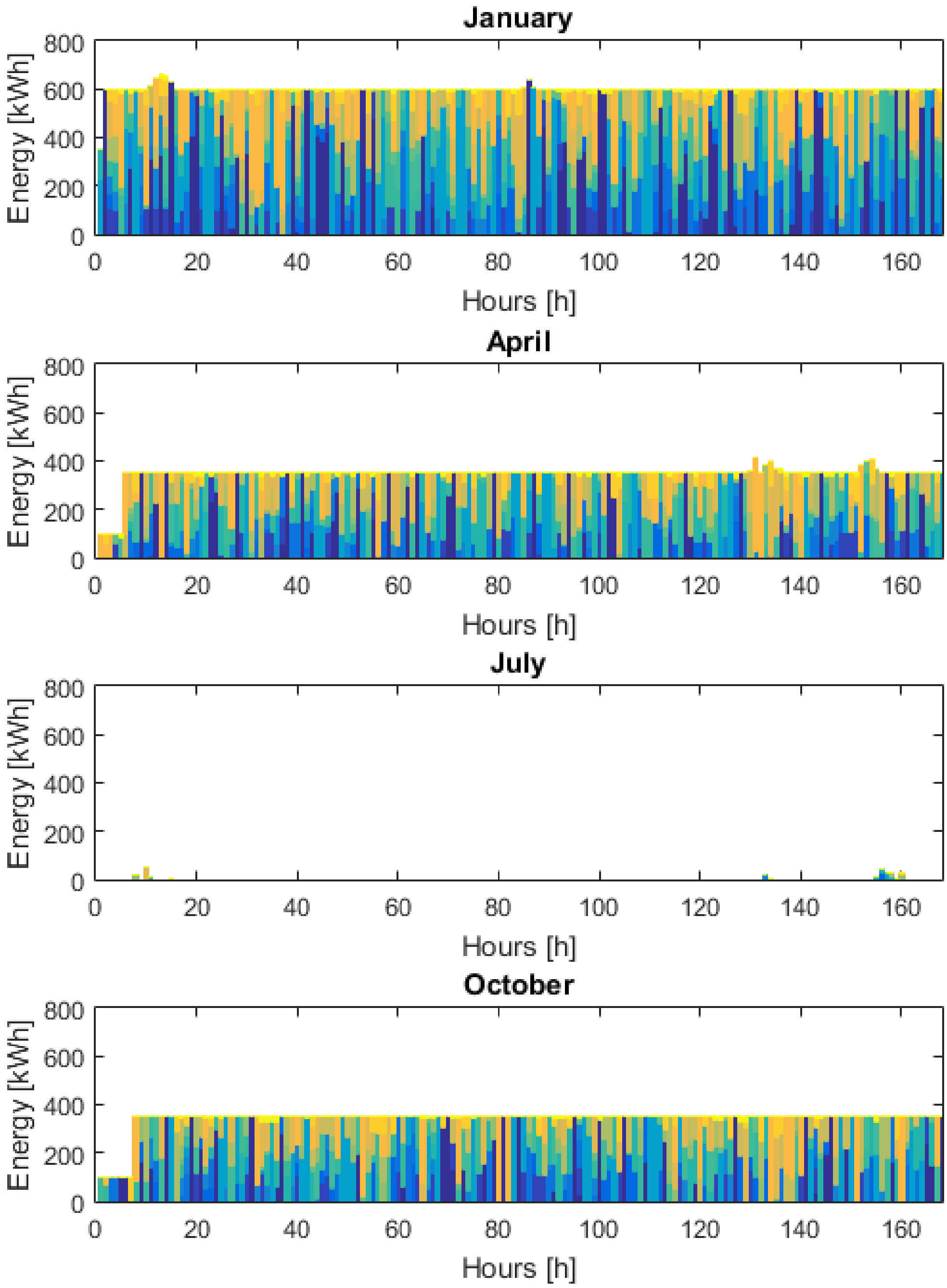

Figure 4.5: Energy bought on the LEM during the different seasons for scenario 1. Each colour represent an agent

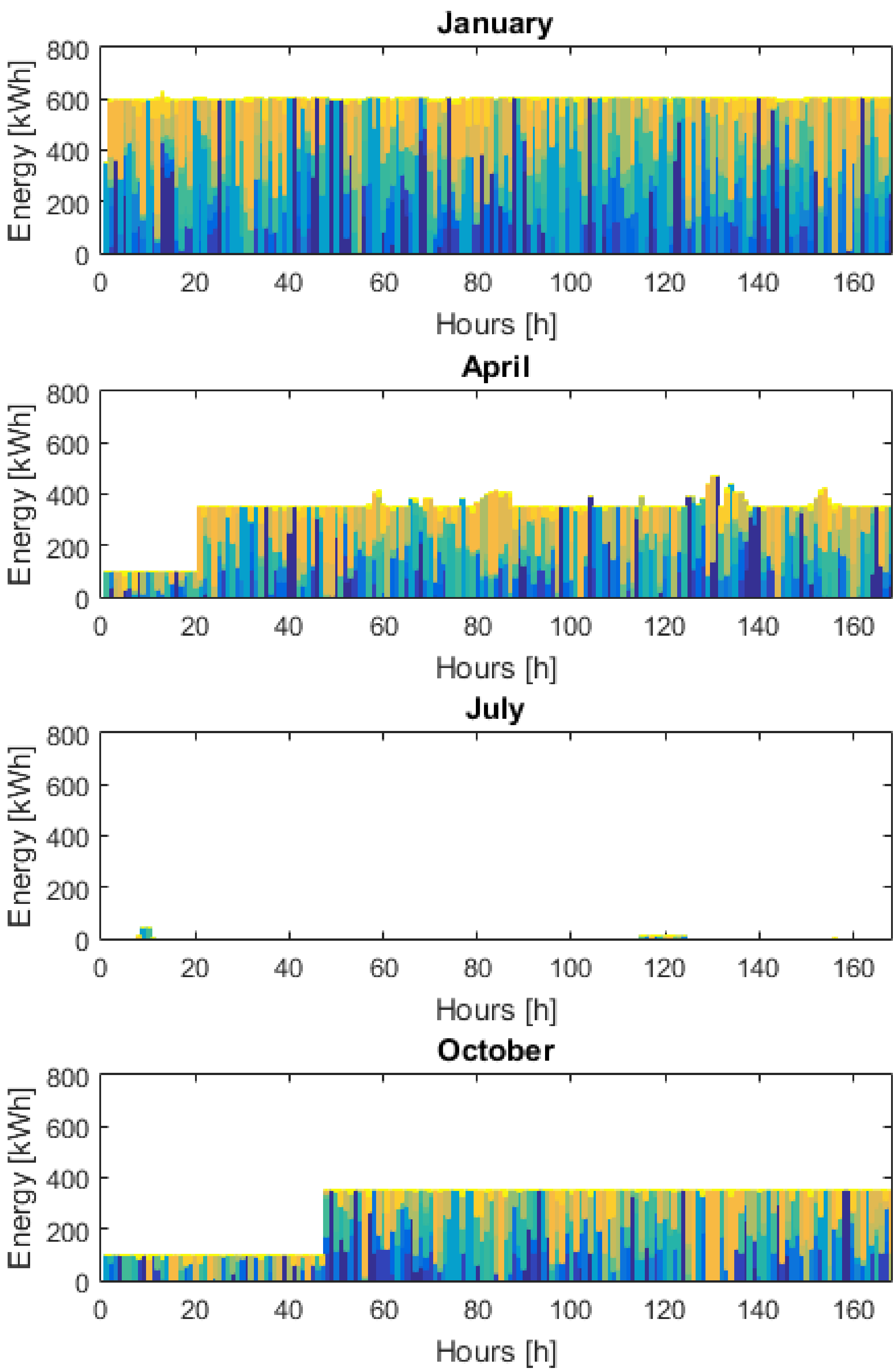

Figure 4.6: Energy bought on the LEM during the different seasons for scenario 2. Each colour represent an agent

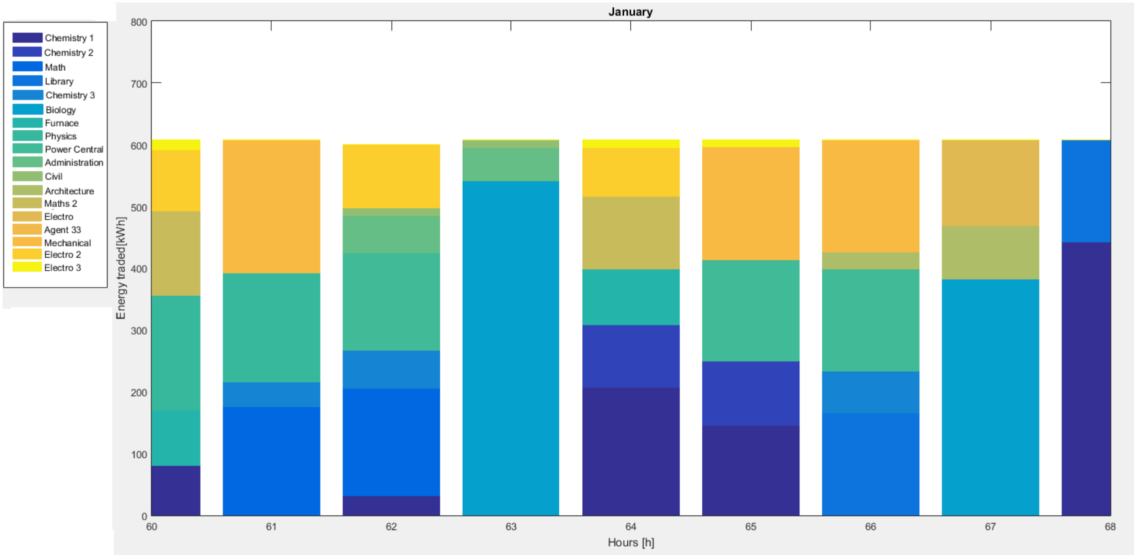

Figure 4.7: Energy bought from the Local Energy Market by the different agents hour 60-68 in scenario 2. Each colour represent an agent.

ates during these periods. This is not the case in July however when the price for heat is so low that the plant is not profitable to run and therefor it is shut down. The price relation between electricity, heat, cost of running and reserve energy is what decides how the CHP will operate, and if different figures for these are used, different result will come out from the model. If the electricity price is increased enough, the CHP will operate throughout the year and not ever on the reserve market which is logical. The CHP will also sell more on the reserve market during January if the reserve prices are increased. The cap of the ramping rate stops the CHP from bidding more on the reserve market during April and October, otherwise it would bid all its capacity on the reserve market. Even though there is a ramp rate constraint on the CHP it might not be realistic since it can react instantly between hours in the model. A cost for ramping is not used in the model which might be the case in reality.

4.2.1 Market Clearing Price Energy Market

The market clearing price is what the market settles the auction on and all energy traded that hour gets a uniform price at that level. Figure 4.11 illustrates how the market price varies during the different seasons for scenario 2 with 20% price difference and 15% forecast error. The price follows the forecast price but at a slightly higher price. During July there is very little trading as seen in figure 4.6, therefore there are only minor parts during the 168 hours where there is an actual market clearing price. The different MCP outcomes during the different scenarios can be compared in Table 4.3 and 4.4.

As can be seen in figure 4.11 and 4.12 the market clearing price is higher than the price that the forecast is based on. The price used as forecast is historical prices from Nordpool. The market clearing price is higher because the price forecast is adjusting the bids both higher and lower than the original forecast. Since some agents will have higher bids they will win the auction. It can be seen in the figure 4.12 that this did not

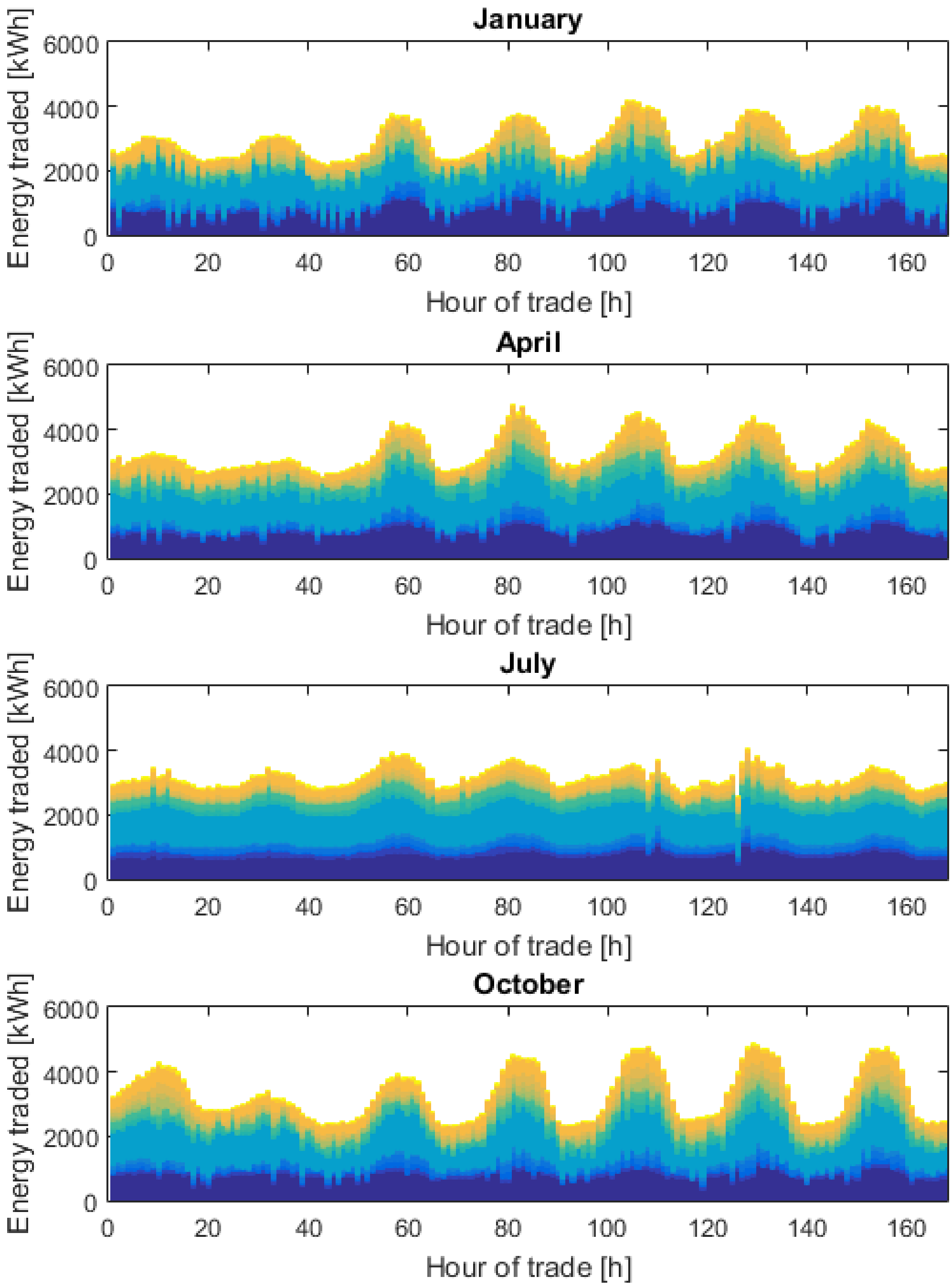

Figure 4.8: Energy bought from Nordpool by the different agents during the base case. Each colour represent an agent

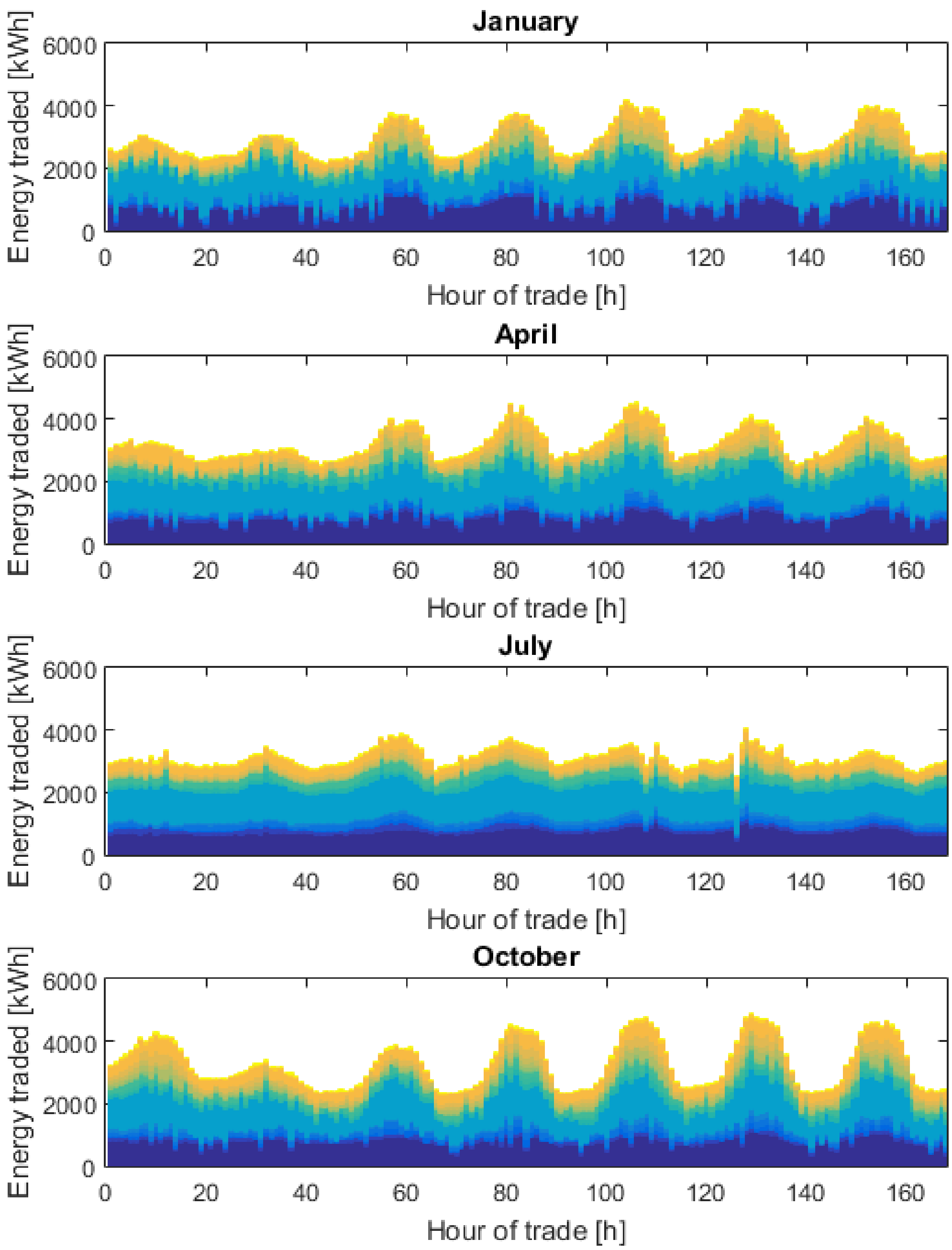

Figure 4.9: Energy bought from Nordpool by the different agents during scenario 1. Each colour represent an agent

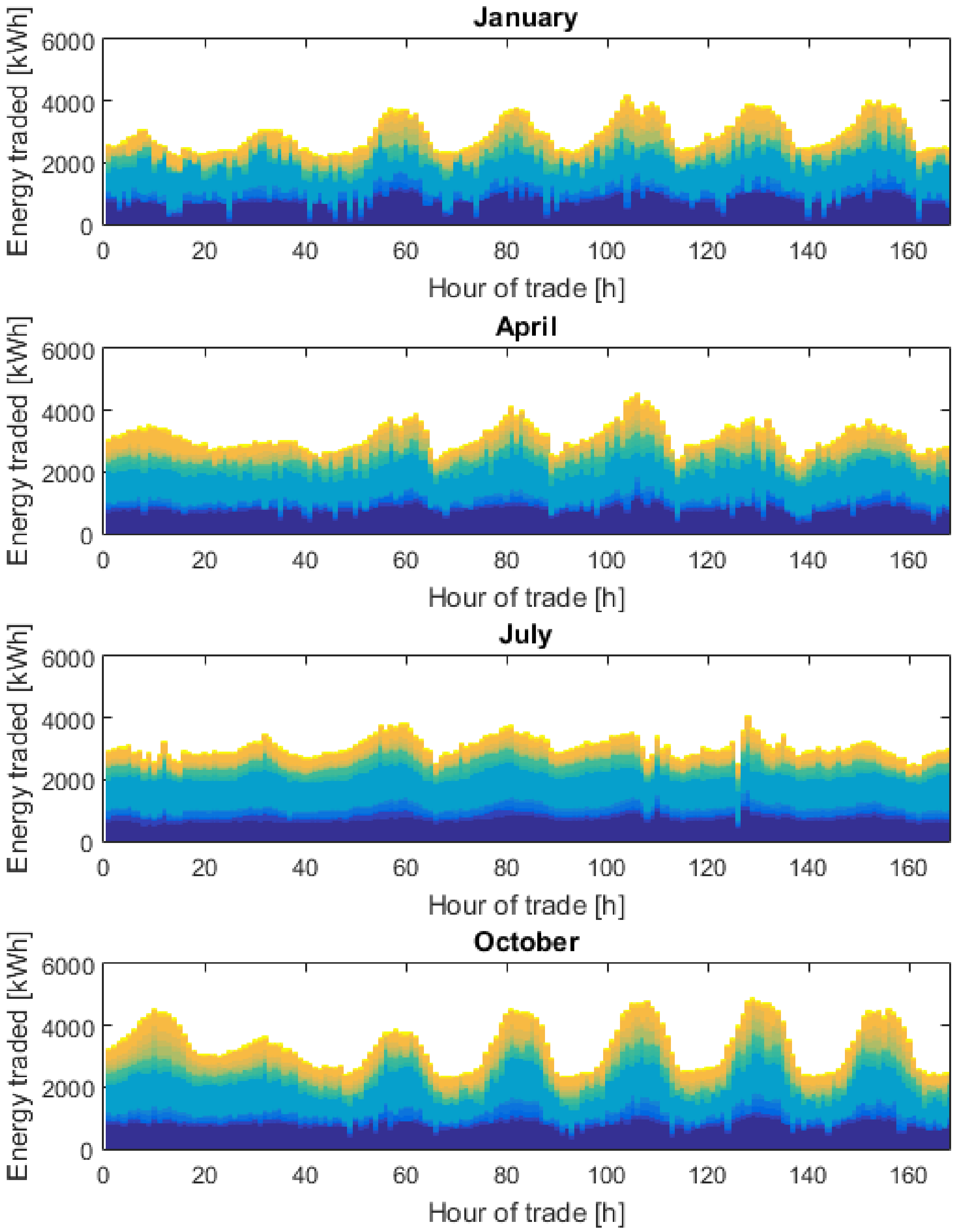

Figure 4.10: Energy bought from Nordpool by the different agents during scenario 2. Each colour represent an agent

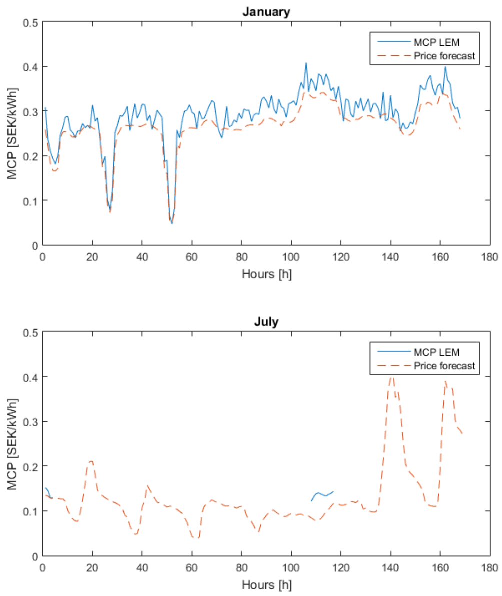

Figure 4.11: Market clearing price and price forecast for scenario 2 with 20% price difference during the different seasons

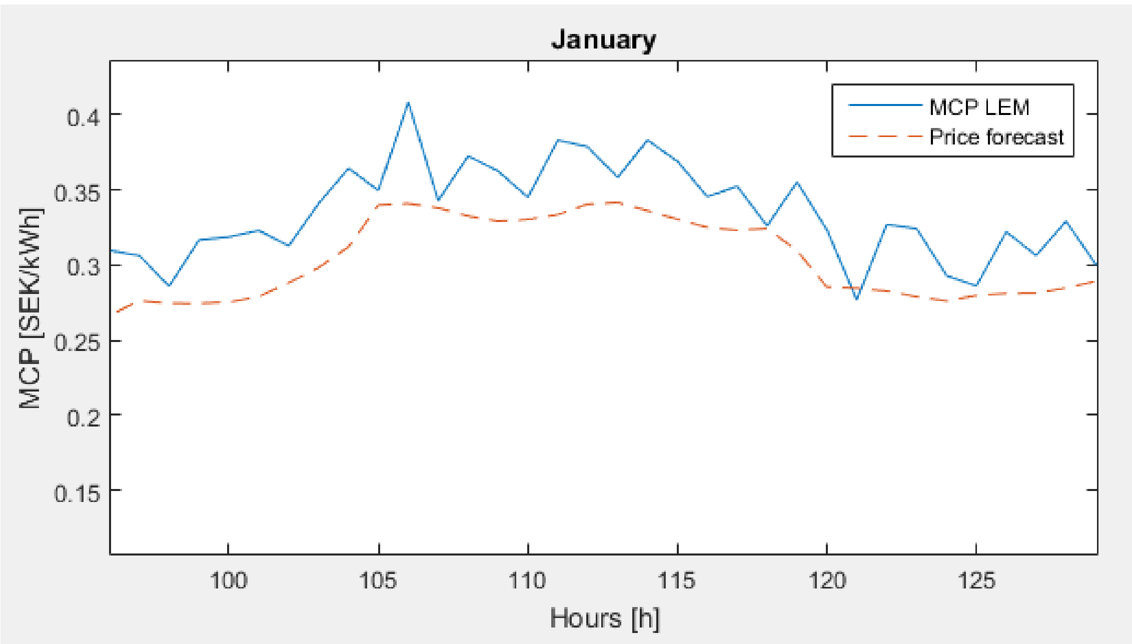

Figure 4.12: Zoomed in sequence of the market clearing price for scenario 2 with 20% price difference in January between hour 100 and 130.

occur once at hour 121. In this hour the last winning bid was actually lower than the forecast price, this is however very unusual. If the price forecast adjustment for every agent would only be lower than the Nordpool the market clearing price on the LEM would always be lower. The model can be manipulated to get a desired result in this sense. If the market model would be implemented in reality the pricing on the market is a major challenge. It does not make sense to trade on a market that is more expensive for an agent that buys power and it would not make sense to sell on a market that pays you less. Therefore the price relation to Nordpool is important. In the model, the agents are forced to trade on the LEM before they can trade with Nordpool.

4.3 24h Service Market

As mentioned in Section 4.2 the different scenarios provide different outcomes from the local energy market. This also include the reserve market. Figure 4.13, 4.14, 4.15 illustrate how much reserve that is sold on the LEM and therefor is available during the different hours. Different colours represent different agents and as can be seen there is one agent that is providing 250 [kWh] multiple times, this is the CHP. It is worth noticing that this is only during April and October. The base case is not able to provide any reserve other than the CHP. In the future scenarios though other agents than the CHP are able to provide reserve energy.

The model also reacts to different forecasts when it comes to how much reserve energy that is predicted to be utilized. The variable K in equation 3.23 is what predicts how much of the reserve energy that will be utilized. In the model this has been set to 1, which means that all energy will be utilized. This would not be the case in reality but in the model it is a way to increase the bids on the reserve market. The profit function for the agents is what is affected and because of this the priority in the agents bids on either the energy or reserve market. Another way to manipulate this is to adjust the prices on both markets. Since the price for being standing reserve is based as a fraction of the historical data from Nordpool as being active reserve this fraction is as easily manipulated as the variable K. Both K and this fraction was set so that agents found it profitable to not only sell energy but also reserve energy. Another important factor for the standing reserve is the demand for the reserve in the auction which is set by the market operator as a fraction of the total demand in the LEM. The market could have a higher demand for reserve and not import as much reserve power from the grid. It is however dependent on the forecast error which might be both higher or lower than the 15% and 5% that are used in the model. Because of this it is important to consider the price for standing reserve and the demand of standing reserve versus the actual need of active reserve and the value for reserve in the case of a real market.

4.3.1 Market Clearing Price Reserve Market

The market clearing price for reserve energy is what the market settles the auction on for all reserve energy that should be available for the energy traded. Figure 4.16 illustrates how the market price varies during the different seasons for scenario 2 with 20% price difference and 15% price forecast error. If comparing the MCP for reserve energy

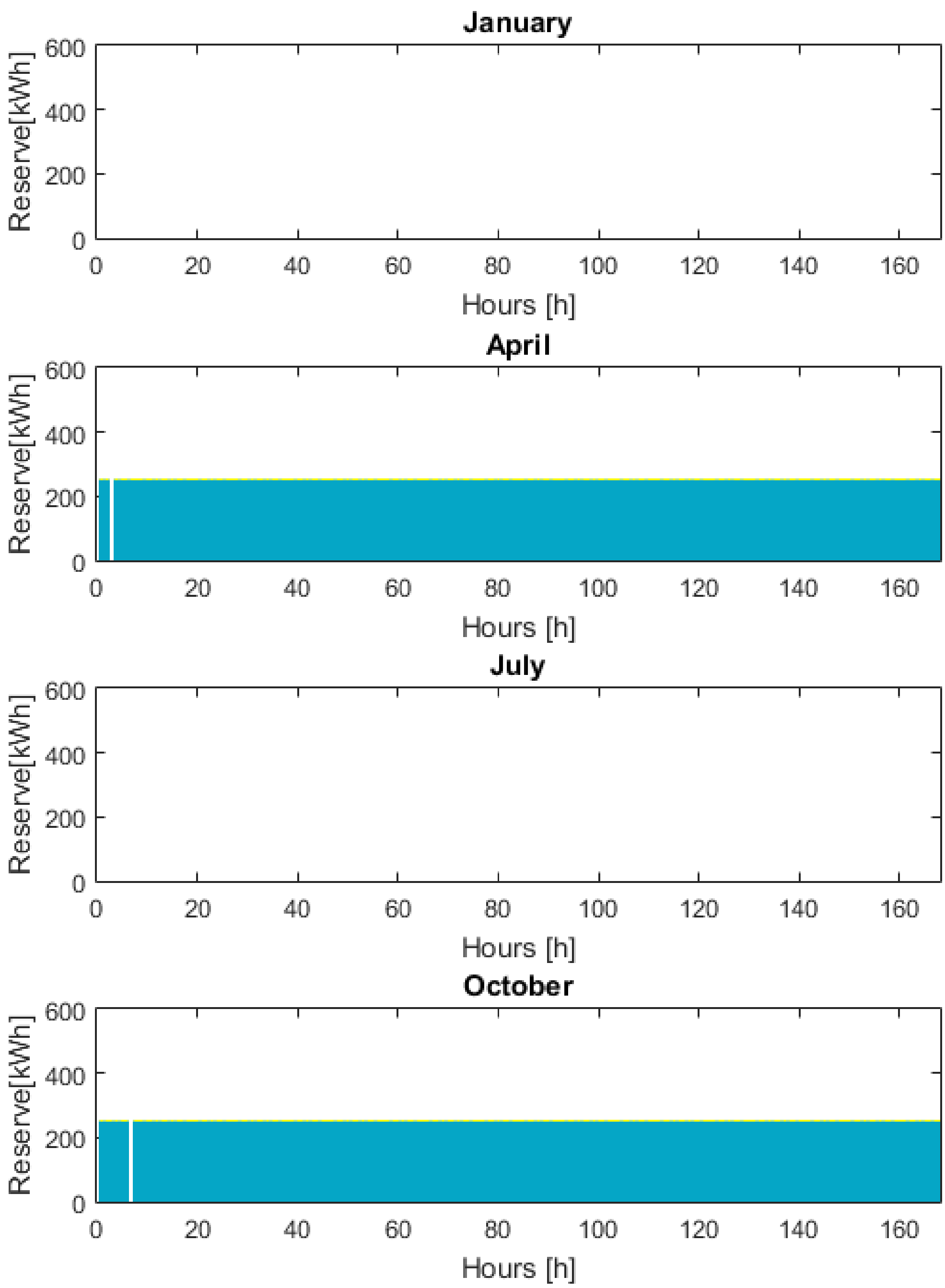

Figure 4.13: Reserve energy sold on the LEM during the different seasons for the base case. Each colour represent an agent.

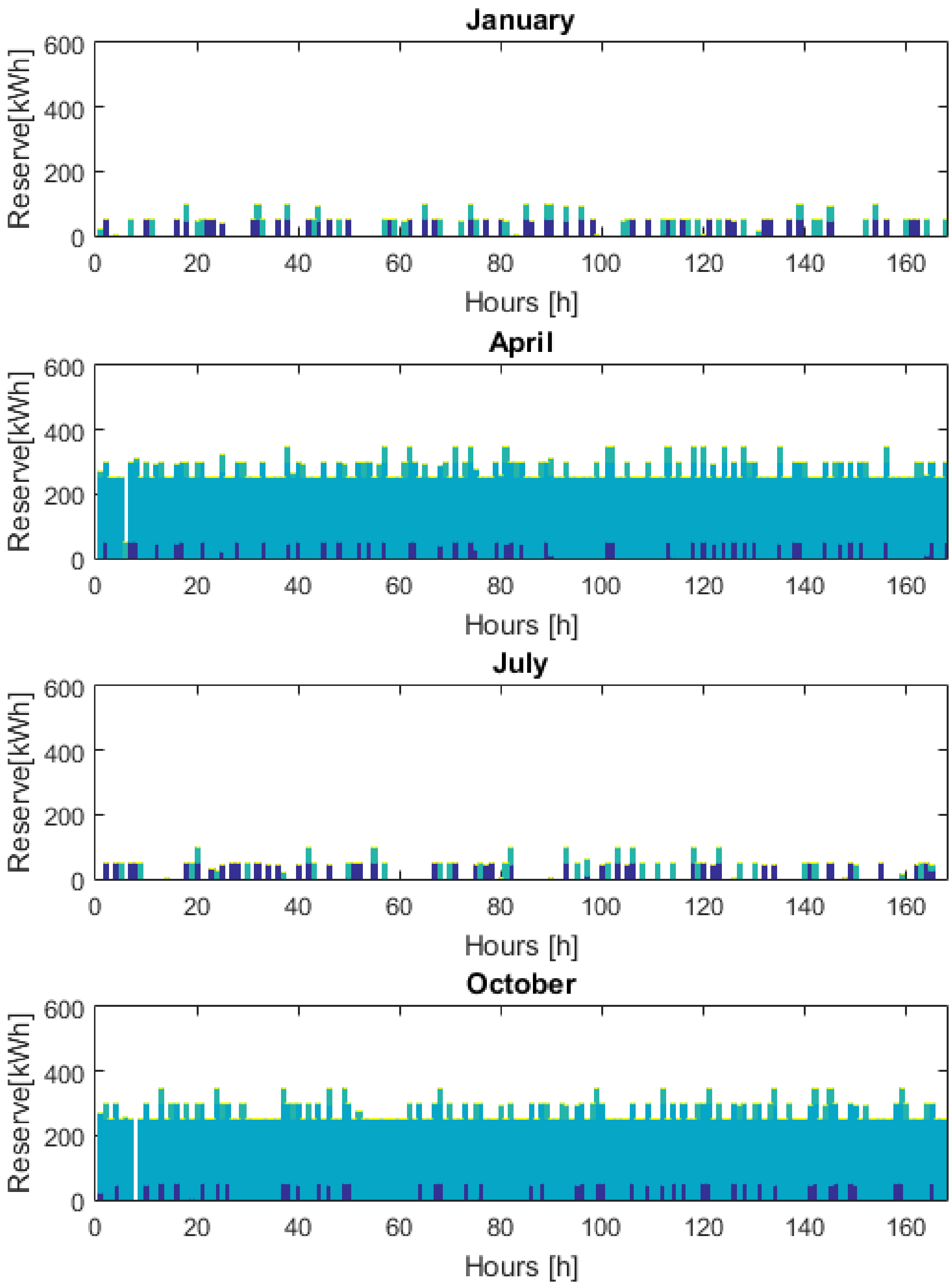

Figure 4.14: Reserve energy sold on the LEM during the different seasons for scenario 1. Each colour represent an agent.

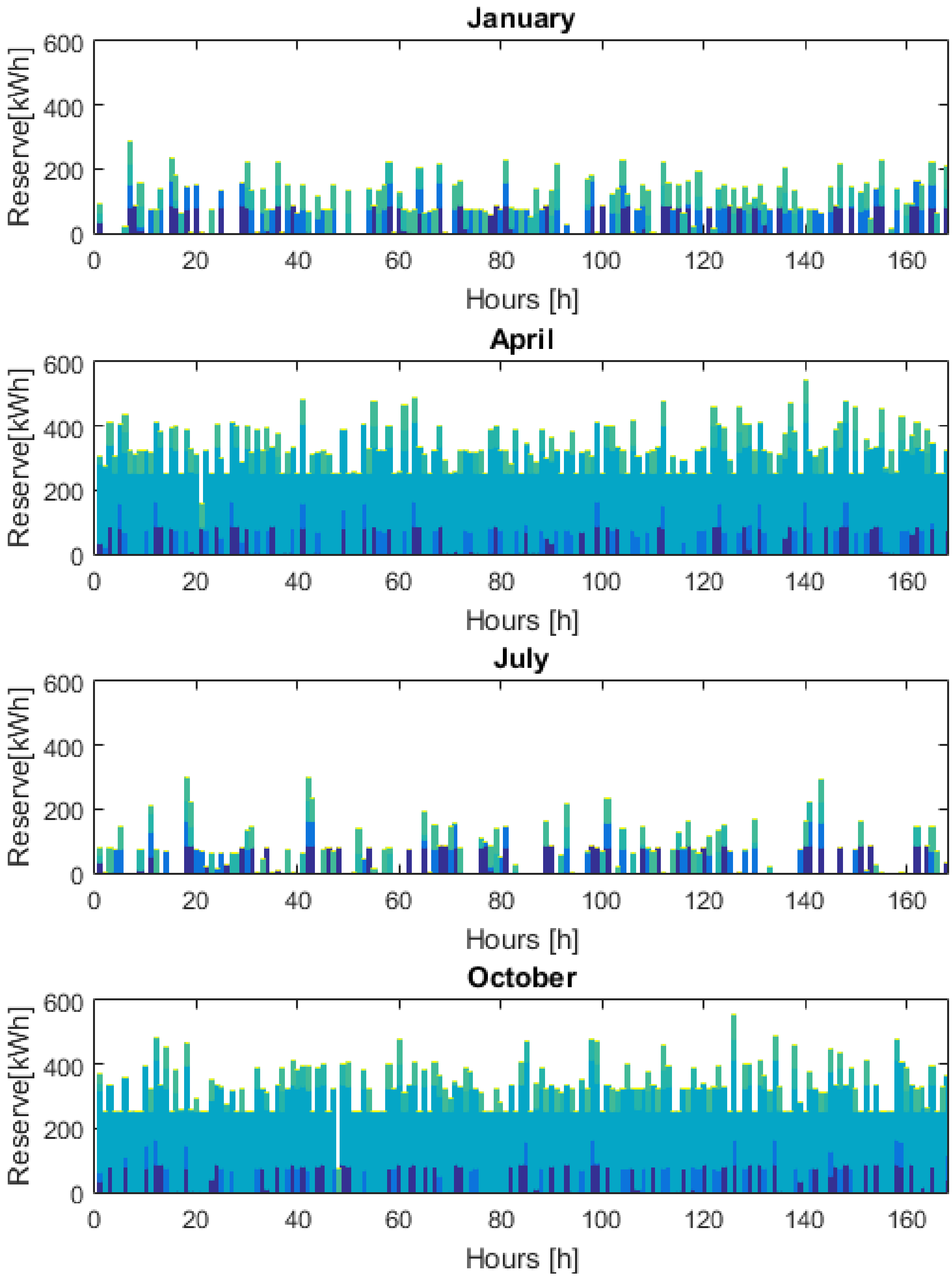

Figure 4.15: Reserve energy sold on the LEM during the different seasons for scenario 2. Each colour represent an agent.

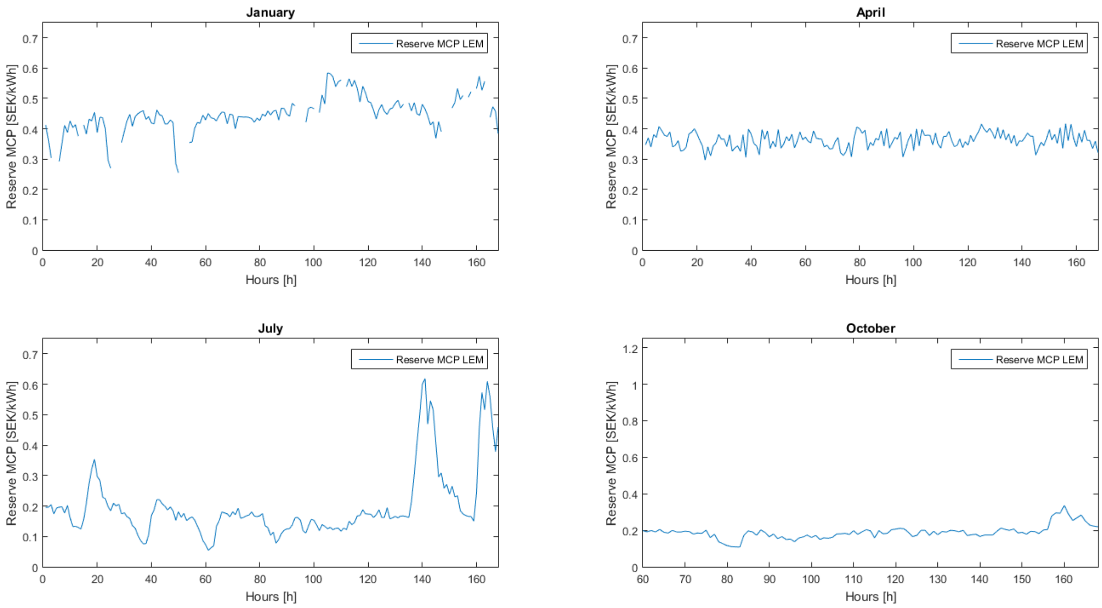

Figure 4.16: Market clearing price for reserve energy for scenario 2 with 20% price difference during the different seasons

that is illustrated in figure 4.16 and the MCP for energy that is illustrated in 4.11 it can be seen that they follow the same pattern and that the difference is that the reserve energy is multiplied with a factor making it more expensive. This is because the price forecast for reserve energy is based on the price forecast for energy. This price relation can be varied in the model to get a desired result. The different clearing prices for the scenarios and seasons are presented in table 4.3 and 4.4.

One of the biggest challenges for the local energy market is the price relationships. Both regarding the internal relationship between the energy and the reserve energy and also the external relationship with the surrounding market. These relationships are what will determine how financially motivated the local energy market is. An agent is not interested in trading on a market with higher price than an alternative market while buying from it and vice veers while selling on it. One of the advantages with the local energy might therefore be the possibility to trade reserve energy but it all comes down to the price of it. These price relations and what different bidding strategies from the agents will have on them are something that needs further investigation.

4.4 Real time market

The auctions that are settled 24 hours before delivery are used when calculating the real time market as described in Section 3.3.3. As described the real time operates with fifteen minute intervals within the hour and balances the forecast errors. In figure 4.17-4.19 the result from the utilization of reserve energy are presented.
As can be seen in figure 4.19 the real time market operates fairly similar in the different seasons. Different colours represent different agents in the LEM that provide reserve energy in the 672 fifteen minute periods. It is worth noticing that the grid provides

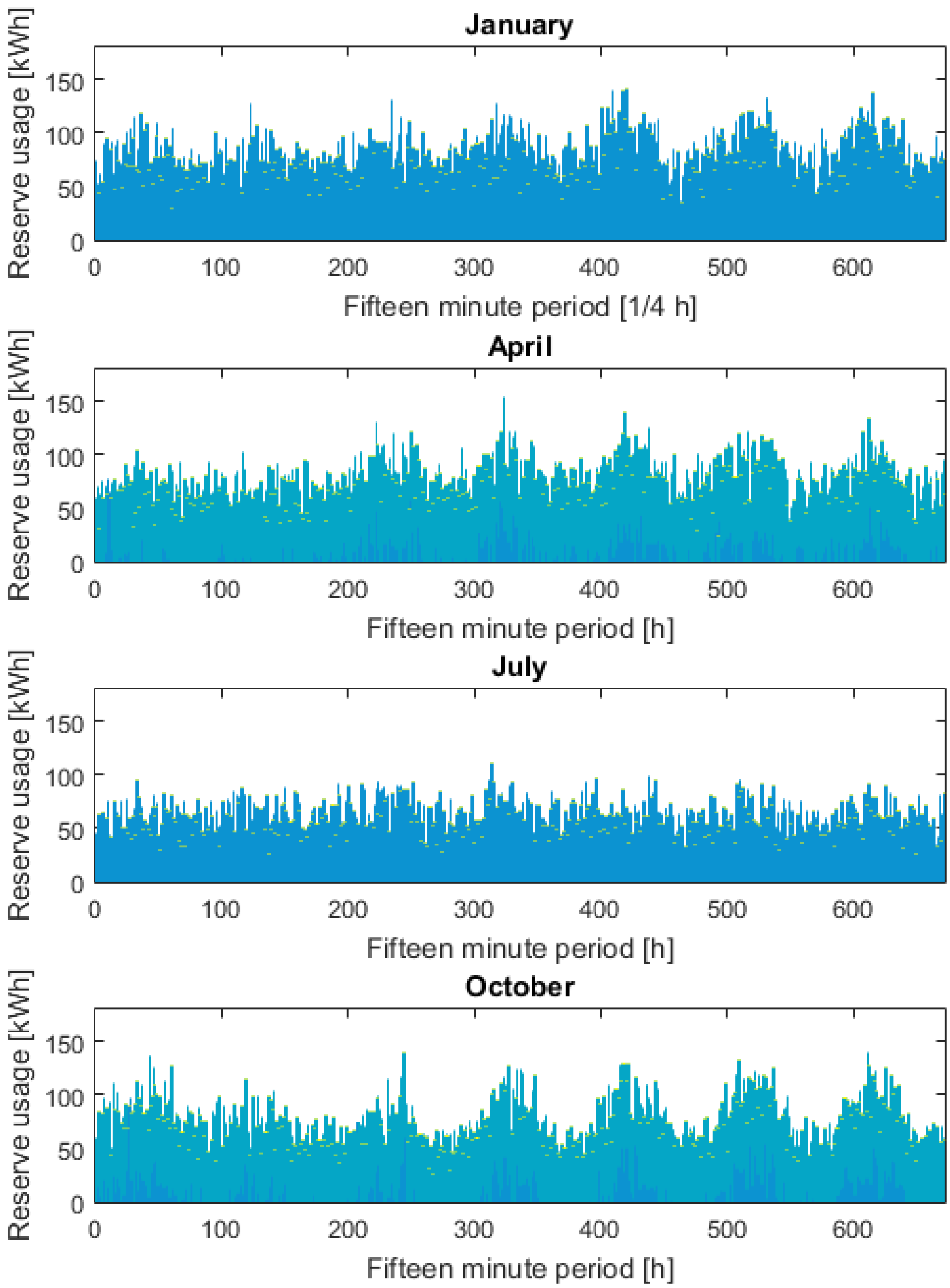

Figure 4.17: Reserve energy utilized during different seasons in the base case. Each colour represent an agent or the grid

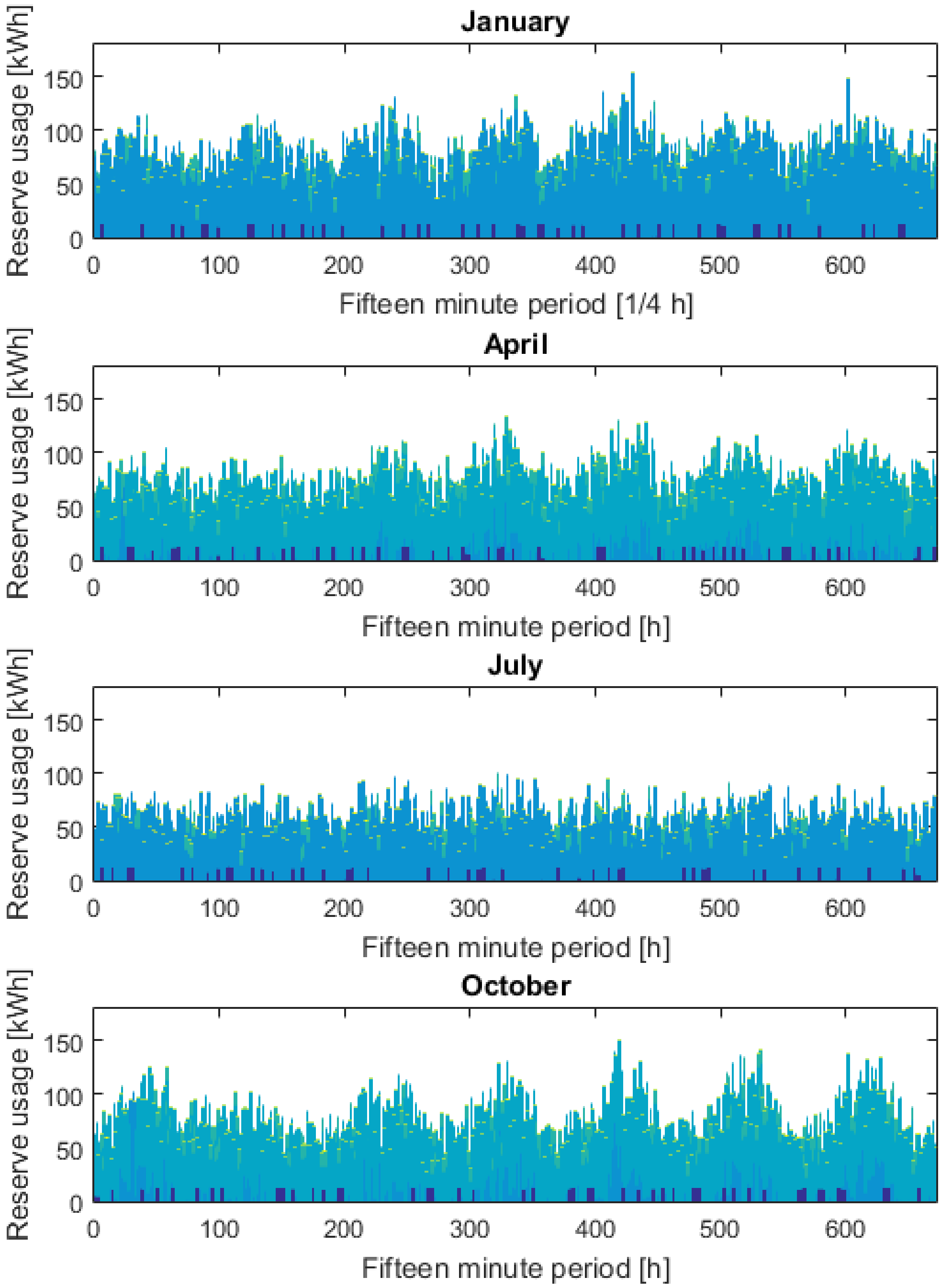

Figure 4.18: Reserve energy utilized during different seasons in scenario 1. Each colour represent an agent or the grid

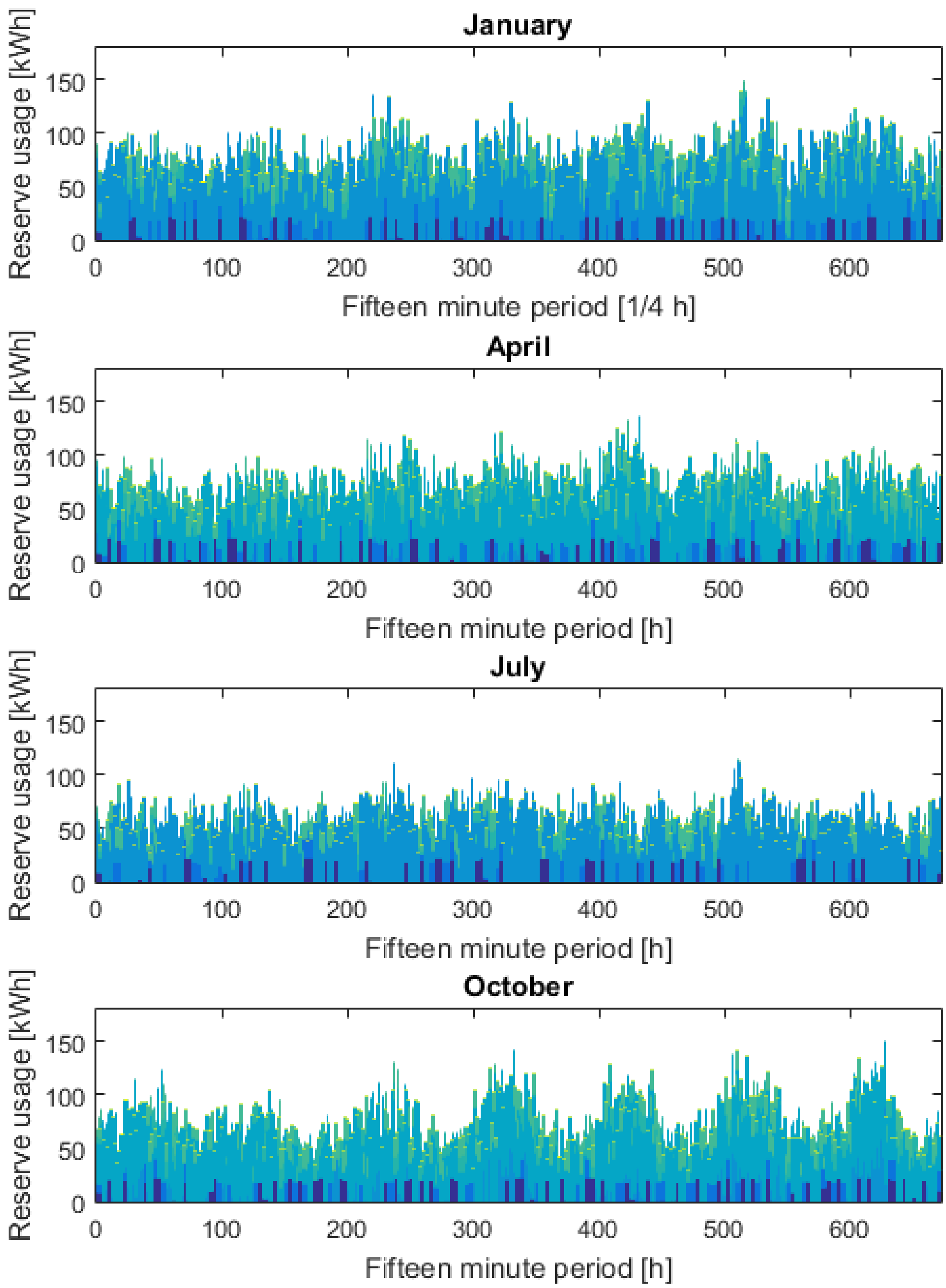

Figure 4.19: Reserve energy utilized during different seasons in scenario 2. Each colour represent an agent or the grid

reserve energy to the LEM. In table 4.2 the amount of reserve energy provided by the agents within the LEM as percentage of the total reserve provided is presented for each case in each month. The lowest amount provided by the LEM is 0% in January and July in the base case and the highest is 93% in April in scenario 2. There are a total of six agents that provide reserve energy at the most. The self provided reserve energy is dependent on the amount of energy equipment in the LEM. Both the batteries and the demand response is vital in order to have a well functioning reserve market.

The designed LEM would be operating both in the energy market and the reserve market. One fundamental aspect of the market is the need for it to be fairly operated and not benefit any market player. The responsibility for the energy and reserve market as well as possibly other ancillary services needs to be addressed by someone. Swedish grid companies have a similar role today where they are not allowed to favour any part and are also responsible for the ancillary service in their own grid. It would therefor be reasonable for a grid company to operate the LEM in their own grid. They would be able to benefit from the ancillary service provided and would be able to optimize the grid they operate in this sense similar to how the market model decide which reserve to priority by using OPF.

Grid companies are not entitled to operate outside their current business domain so it might be difficult legally if the law is not adapted. If the grid companies would not be responsible another suggestion is for Nordpool to be responsible for the markets. It might seem unreasonable for Nordpool to do so as it complicates their operations. The benefits from the LEM are as discussed maybe not a lower electricity price since trading in a market where you make less or lose more does not make sense for the agents. The benefits might be more related to ancillary services and to adapt to forecast errors easier. If Nordpool could benefit from this as well is debatable. A third option would be for a new organization to be responsible for the markets. They would be closely linked with both the grid company and Nordpool and would act to benefit the LEM. Neither of the suggestions have a clear advantage and this would need further investigation. It is however not what seem to be the biggest challenge for a LEM as pricing, forecasts and profit from operating on a LEM is major challenges.

4.5 Scenario comparison

The three different scenarios and the two different price forecast factor differences are summarized and presented in the two Tables 4.4 and 4.3. The positions in these Tables that are marked with "-" means that no transactions in the market where made during the period. Worth noticing is that when the price fluctuations are 20% less energy is traded than when the fluctuations are 10%. The average MCP is also lower in the case with 10% price factor difference. The amount of reserve energy traded is however fairly similar but the average MCP is a bit lower in the case with 10% fluctuations. The amount of energy traded with Nord Pool however is lower when there is a 20% price fluctuation. Worth noticing is also that the amount traded whitin the LEM is about 10% of the amount bought from Nord Pool for all scenarios.

The Real time market depends on the traded energy from the energy and reserve market from the 24 hours market. The intra day market decides on which agent to provide the reserve energy through an OPF where the objective is tom minimize the losses. The losses in the grid are presented in Table 4.5. The Table presents the total losses for all four weeks for the different scenarios, different price fluctuations and different forecast errors in the predicted demand. Worth noticing is that the higher the forecast error is the higher the losses are. The losses also decrease with more energy equipment in the system.

Table 4.3: Price difference of 20 %

Scenario	Month for simulated week	Average MCP for energy market [SEK/KWh]	Average MCP for Reserve market [SEK/KWh]	Energy Traded within Market [MWh]	Energy traded with Nordpool [MWh]	Reserve Energy Traded [MWh]
Base case	January	0.2941	-	100.55	501.5	-
	April	0.2667	0.3734	58.3	558.2	41.75
	July	-	0.203	0	535.9	42
	October	0.150	0.211	57.3	557.7	41.75
	Average	0.2369	0.2625	54.1	538.3	41.83
	Total	0.711	0.7874	216.15	2153	125.5
Scenario 1	January	0.2936	0.4589	100.8	498.8	4.32
	April	0.2691	0.3697	57.91	544.8	46.3
	July	0.1334	0.2018	0.2487	527.9	45.8
	October	0.1521	0.2088	57.05	556.8	45.9
	Average	0.2120	0.3098	54	532.1	35.6
	Total	0.8482	1.239	216	2128	142.4
Scenario 2	January	0.2911	0.4475	101.5	493.9	15.1
	April	0.2685	0.3627	55.6	531.5	56.1
	July	0.1359	0.1997	0.217	517.6	52.1
	October	0.1530	0.2044	47.05	565.4	55.7
	Average	0.2121	0.3036	51.10	527.1	44.7
	Total	0.8485	1.2142	204.4	2108	178.8

Table 4.4: Price difference of 10 %

Scenario	Month for simulated week	Average MCP for energy market [SEK/KWh]	Average MCP for Reserve market [SEK/KWh]	Energy Traded within Market [MWh]	Energy traded with Nordpool [MWh]	Reserve Energy Traded [MWh]
Base case	January	0.2803	-	100.55	501.5	-
	April	0.2561	0.3563	16.8	599.7	42.0
	July	-	0.1978	-	535.9	42
	October	0.1452	0.2002	16.8	598.2	42.0
	Average	0.2272	0.1885	33.54	558.8	31.5
	Total	0.6817	0.7543	134.15	2235	126.0
Scenario 1	January	0.2783	0.4256	100.8	499.03	4.01
	April	0.2568	0.3544	17.16	585.9	46.7
	July	0.1259	0.1963	0.2487	528.1	45.9
	October	0.1448	0.1998	16.8	597.14	46.1
	Average	0.2015	0.2940	33.75	552.55	35.7
	Total	0.8058	1.1761	135	2210	142.8
Scenario 2	January	0.2789	0.4215	100.6	495.2	15.7
	April	0.2567	0.3536	18.3	569.3	57.5
	July	0.1257	0.1956	0.2174	517.8	53.4
	October	0.1451	0.1979	16.8	595.8	55.4
	Average	0.2016	0.2922	33.97	544.5	45.5
	Total	0.8064	1.1687	135.9	2178	182.1

The energy traded within the LEM is not changing significantly during the different scenarios which also can be seen in 4.4 and 4.3. This is also illustrated in figure 4.4-4.6. This means that the agents cover their own demand first and store energy during high production hours. This is also something that indicate that the agents behaves as intended. The difference is as mentioned a lower trade with Nordpool. The figures 4.8-4.10 show that the import from Nordpool looks fairly similar during the different seasons and scenarios. One could argue that the LEM would be more efficient by reducing the peaks more efficiently. The agents are not optimized with a peak tariff but an energy tariff, resulting in a minimization of interaction with the grid but without regards to the peak power. This is something that could be improved with the market model. When designing the market a clever way to price the market resulting in a collaboration in reducing the main connection point to the grid would also be a cheaper market in reality but there are difficulties designing such market making it fair and competitive.

Table 4.5: Real time market losses

	Base case			
	10% Price		20% Price	
	5% Forecast	15% Forecast	5% Forecast	15% Forecast
Total losses in LEM [kW]	**583.7**	**606.2**	**582.3**	**604.3**
	Scenario 1			
	10 % Price		20 % Price	
	5 % Forecast	15 % Forecast	5 % Forecast	15 % Forecast
Total losses in LEM[kW]	**580.8**	**602.6**	**579.0**	**601.2**
	Scenario 2			
	10 % Price		20% Price	
	5 % Forecast	15 % Forecast	5 % Forecast	15 % Forecast
Total losses in LEM [kW]	**574.3**	**595.3**	**572.7**	**594.2**

5
Conclusion and Future Work

5.1 Conclusions

This thesis focused on three different main objectives. The following conclusions can be made:

- **With regard to establishing a Market for Energy Trading**
  - The designed market trades both energy and reserve energy and has the ability to compensate for its own imbalances upon delivery.
  - The designed market was highly dependent on the market player's ability to consider many aspect such as predicted price, need of reserve, production and demand and based on this make well balanced bid decisions.
  - The market is also dependent on major investments in energy equipment in order to have a significant impact.
  - The suggested market is connected to a surrounding market, which is assumed to be Nordpool in this case, and is highly dependent on that market in order to meet the participants needs. One of the major challenges with the local energy market is the price relation to the surrounding market.

- **With regard to design of a Computational Model**
  - The computational market model was designed using GAMS for the market operations and Matlab and Excel to handle and store the data.
  - The computational model was designed so that it can easily adapt to different grids and agents.
  - The computational model reacted logically to different assumptions regarding price forecasts and energy equipment inventory.

- **With regard to test the Model with Data from the Chalmers Campus**
  - The computational model used Chalmers campus Johanneberg's grid and buildings during the simulations. Data regarding solar irradiation and building demand was simulated from real data collected in 2016.
  - Three different scenarios regarding energy equipment was simulated. One with today's equipment and two with more investment in battery, solar PV and demand response.
  - Every investment scenario was simulated for one week in the four months January, April, July and October.
  - The results showed that the local energy market was not able to provide itself with the required energy. The agents bought about 10% of their total

consumption from the local energy market in all simulated investment scenarios, the rest was provided by the grid.
– The biggest difference between the scenarios was the amount of reserve energy provided by the local energy market. In the investment scenario with most energy equipment the local energy market provided an average of 59% of the reserve energy needed. In the investment scenario with least energy equipment the amount of reserve energy provided was an average of 38%.
– The market clearing price is not affected by the amount of energy traded but the bids, i.e. the price forecasts, made by the agents.

5.2 Future Work

- *Bidding strategies* - The market has not been tested when the market players use different bidding strategies. The current model base the bids on the same price forecast and it would be interesting to see how the market behaves when different price forecasts are used for different agents. More sophisticated bidding strategies by the agents would also be interesting to model.

- *Interaction with other markets* - Improved interaction with larger energy markets such as Nord Pool, to distinguish how the price correlation are connected.

- *Pricing mechanism* - The pricing and the advantages of trading on a LEM is something that needs further work. One advantage with the LEM is the possibility to have ancillary services on the LEM. The current model has reserve energy but it would be interesting to involve other services as well. The pricing of these services and thereby the advantages of having them is also something that needs to be investigated further.

- *Demand response* - Further investigation on the flexible load possibilities. The model would be improved if every market player had a more realistic and individual demand response possibilities.

- *Cost and investment analysis* - This thesis have not included investment costs in the different scenarios which would have an impact in how beneficial the LEM is. This would be interesting to compare to the current energy trading system and other possible trading options for the future.

- *Taxes and peak power cost* - Including taxes and peak power costs in the market model would give a more accurate representation with the comparison with the energy costs.

- *Improve data* - Make the model more realistic by making the data more accurate and with increased resolution. This include solar production, demand of the different buildings and the possibility for demand response.

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A

Appendix 1

A.1 GAMS Code - Market player

```
set h hours /1*24/
set PR data /PRi,Pry,K,L,PryR/
set t timmar  /1*24/
set COM data /Bi,Si,By,Sy/

parameter
Pemax(h)            Maximum discharge battery
inBat(h)
By(t)
Sy(t)
PRi(h)
Pry(h)
K(h)
PryR(h)
Dem(h)
Pprod(h)
Pvent(h)
SP(h)               Spot price(Same as PRi)
CPEn(h)             Cost of energy production
CRSe(h)             CRSe is the cost of being a reserved energy
PPSe(h)             PPSe is the profit form using reserved energy
CPSe(h)             CPSe is the cost of using reserved energy
rup                 Ramp up constraint
rdown               Ramp down constraint
ProdCom
CHPcom(h)
SOCcom(h)
Emax(h)
HeatToPower(h)
HeatPrice(h)
PrespCom(h)
;
```

```
scalar
chr        efficiency of energy storage    /0.95/
dis        efficiency of energy storage    /0.95/

;
positive variable
PEn(h)
PSe(h);
variable
*Profit from prodution
profit
;


$GDXIN C:\Users\MyUser\Desktop\MasterThesis\Marketplayers.gdx
$LOAD Pvent=P_fan
$LOAD Pemax=disMax
$LOAD Emax=Pmaxb
$LOAD SOCcom=SOC
$LOAD CHPcom=CHPconst
$LOAD Dem=P_dem_m
$LOAD By=By
$LOAD Sy=Sy
$LOAD PRi=Pri
$LOAD Pry=Pry
$LOAD K=K
$LOAD PryR=Pryr
$LOAD Pprod=P_pv
$LOAD SP=PRi
$LOAD CPEn=CPEn
$LOAD CRSe=CRSe
$LOAD PPSe=PPSe
$LOAD CPSe=CPSe
$LOAD rup=Rup
$LOAD rdown=Rdown
$LOAD max=CHPmax
$LOAD HeatToPower=H_t_P
$LOAD HeatPrice=Heatprice
$LOAD PrespCom=Presp
$GDXIN

VARIABLES
SOC(h)          state of charge at bus i
Pec(h)          charge power from ess
Ped(h)          discharge power from ess
```

```
Qbatt(h)
profit
Pedi(h)
Pedy(h)
Imp(h)
Exp(h)
EnIncV(h)
EnCoV(h)
SeIncV(h)
SeCoV(h)
Prespons(h)
PeakPower
SoldHeat(h)
Solvariabel(h)
;
binary variables
u(h)
v(h)
;
positive variable
PEn(h)
PSe(h);

EQUATIONS
SOC1(h)             of SOC
ChargeEq(h)         Charging Equation
ProfitFunc          Profit function
MC(h)               Market choise for battery
ChargeiEq(h)        Charging energiy
ChargeyEq(h)        Charging service
SOC2(h)
Import(h)           Import
Export(h)           Export
const(h)            CHP production constraint
rampup(h)           Ramp up constraint for CHP
rampdown(h)         Ramp down constraint for CHP
EnInc(h)            Income from energy
EnCo(h)             Cost from energy
SeInc(h)            Income from service
SeCo(h)             Cost from service

SoldComUpCHP (h)
SoldComDownCHP (h)
DReq(h)             Demand response equation
DReq2(h)
DReq3(h)
```

```
DReq4(h)
constResChp(h)
PeakEQ(h)
SoldHeatEQ(h)
SolEqVar(h)
;

SolEqVar(h)..
Solvariabel(h)=e=Pprod(h);

*-----------------------------------------------------------------*
*BATTERY CONSTRAINS
*Limitation of charging up and down
Qbatt.up(h) = 0.3*Pemax(h);
Qbatt.lo(h) = -0.3*Pemax(h);

*Limits for state of charge
SOC.up(h) = 1;
SOC.lo(h) = 0;

*Charging and discharging limits
Ped.up(h) = Pemax(h);
Ped.lo(h) = 0;
Pec.up(h) = Pemax(h);
Pec.lo(h) = 0;

Pedi.up(h) = Pemax(h);
Pedi.lo(h) = 0;
Pedy.up(h) = Pemax(h);
Pedy.lo(h) = 0;

*Pec and Ped can't operate during the same hour
ChargeEq(h)..
Pec(h)*Ped(h) =l= 0;
ChargeiEq(h)..
Pec(h)*Pedi(h) =l= 0;
ChargeyEq(h)..
Pec(h)*Pedy(h) =l= 0;


*Charging equations
* Change of SOC
SOC1(h)\$(ord(h) ne 1)..
SOC(h) =e= SOC(h-1)
+((chr*Pec(h-1))/(Emax(h)))-(Ped(h-1)/(Emax(h)));
```

```
*Initial value of battery
*SOCcom is the commitment that is received from previous hour
SOC2(h)\$(ord(h) eq 1)..
SOC(h)=e=SOCcom(h);


*Market choice for battery
MC(h)..
Pedi(h)+Pedy(h)=e=Ped(h);



*-----------------------------------------------------------------------------*
*CHP  CONSTRAINS
const(h)..
PEn(h)+PSe(h)=l=max(h);

constResChp(h)..
PSe(h)=l=rup(h);

*Ramp up depending on ramping and commitments
rampup(h)\$(ord(h) ne 1)..
(PEn(h)-PEn(h-1)-PSe(h-1))=l=rup(h)*u(h);

SoldComUpCHP(h)\$(ord(h) eq 1)..
PEn(h)=l=rup(h)+CHPcom(h)-PSe(h);


*Ramp down depending on ramping and commitments
rampdown(h)\$(ord(h) ne 1)..

(PEn(h-1)-(PEn(h)))=l=rdown(h)*u(h);

SoldComDownCHP(h)\$(ord(h) eq 1)..
PEn(h)=g=CHPcom(h)-rdown(h);

SoldHeatEQ(h)..
SoldHeat(h)=e=PEn(h)*HeatToPower(h);

*-----------------------------------------------------------------------------*
*DEMAND RESPONSE CONSTRAINTS
Prespons.lo(h) = 0;
Prespons.up(h) = Pvent(h);

*Limits the flexible load to every other hour
DReq(h)\$(ord(h) ne card(h))..
```

```
Prespons(h)*Prespons(h+1)=l=0;

*Limits the flexible load to every other hour
DReq2(h)\$(ord(h) ne card(h))..
Prespons(h)*Prespons(h+2)=l=0;

DReq3(h)\$(ord(h) eq 1)..
Prespons(h)*PrespCom(h)=e=0;

DReq4(h)\$(ord(h) eq 2)..
Prespons(h)*PrespCom(h)=e=0;

*--------------------------------------------------------------------------*
*Peak power
PeakEQ(h)..
PeakPower =g= Exp(h) ;

*--------------------------------------------------------------------------*
*PROFIT FUNCTIONS
*Import and export function.

Import(h)..
Imp(h)=e=Pec(h)+Dem(h)-Pprod(h)-Pedi(h)-PEn(h) ;

Export(h)..
Exp(h)=e=Pprod(h)+Pedi(h)+PEn(h)-Pec(h)-Dem(h);

*Energy Profit function
EnInc(h)..
EnIncV(h)=e=Pri(h)*Exp(h)+SoldHeat(h)*HeatPrice(h);

*Energy Cost function
EnCo(h)..
EnCoV(h)=e=CPEn(h)*PEn(h);

*Service market profit
SeInc(h)..
SeIncV(h)=e=(PSe(h)+Pedy(h)
+Prespons(h))*PPSe(h)*K(h)+(PSe(h)
+Pedy(h)+Prespons(h))*PryR(h)*(1-K(h));

*Service market cost
SeCo(h)..
SeCoV(h)=e=PSe(h)*(CRSe(h))*((1-K(h))+K(h)*CPSe(h)) ;

*Profit as a function of energy markets and service markets
```

```
ProfitFunc..
profit=e=sum(h,EnIncV(h)
-EnCoV(h)+SeIncV(h)-SeCoV(h))-PeakPower*0.27;

model BatteryFil /all/;

solve BatteryFil using MINLP maximizing profit;
display
profit.l
Ped.l
Pedi.l
Pedy.l
Pec.l
SOC.l
PSe.l
By
Sy
Imp.l
Exp.l
PEn.l
Dem
u.l
Prespons.l
Pvent
EnIncV.l
EnCoV.l
SeIncV.l
SeCo.l
PeakPower.l
SoldHeat.l
Solvariabel.l

;

execute_unload 'Marketplayers2',PEn,Solvariabel,
PSE,SOC,Profit,Pedi,Pedy,Ped,Pec,Exp,Dem,
By,Sy,Pprod,Prespons,PeakPower,SoldHeat,EnCoV,SeCoV,profit;
```

A.2 GAMS Code - Energy Market 24 Hours

```
set j /1*41/


parameter
DemandE(j)
DemandB(j)
SupplyE(j)
Supply1E(j)
Supply2E(j)
Supply3E(j)
Supply1P(j)
Supply2P(j)
Supply3P(j)
SupplyB(j)
Pmin(j)
;

$GDXIN C:\Users\MyUser\Desktop\MasterThesis\MarkEnergy.gdx
*Demand Energy and bid
$LOAD DemandE=P_df
$LOAD DemandB=B_d_p
$LOAD SupplyE=P_sp
$LOAD Supply1E=B_1_E
$LOAD Supply1P=B_1_P
$LOAD Supply2E=B_2_E
$LOAD Supply2P=B_2_P
$LOAD Supply3E=B_3_E
$LOAD Supply3P=B_3_P
$LOAD Pmin=Pmin
$GDXIN
;



Variable
benefit total profit
;

binary variable
*Generators offer
W1(j)
U1(j)
U2(j)
```

```
*Startup
UST(j)
;

positive variable
P_s(j)
P_chp(j)
P_b(j)
produced
COSTB
COSTG

P_sun(j)
P_bat(j)
CHPprod(j)
;

EQUATIONS
obj
const1(j)
DSB
supply
Cob


CHPprodEQ(j)
;

*Constrain on Generation for CHP
const1(j)..
P_chp(j)=l=W1(j)*(Supply3E(j)-Pmin(j));



P_b.up(j)=DemandE(j);




supply(j)..
produced(j)=e=(((W1(j)*Pmin(j))+P_chp(j))+P_bat(j)+P_sun(j));

*Demand-supply balance
DSB..
sum((j),(((W1(j)*Pmin(j))+P_chp(j))
+P_bat(j)+P_sun(j)))=e=sum((j),P_b(j));
```

```
*Objective function includes start-up cost
obj..
benefit=e=sum((j),DemandB(j)*P_b(j))
-sum((j),(P_sun(j)*Supply1P(j))
+(P_bat(j)*Supply2P(j))
+(Supply3P(j)*((W1(j)*Pmin(j))+P_chp(j))));


*market price
Cob..
COSTB=e=sum((j),DemandB(j)*P_b(j));

CHPprodEQ(j)..
CHPprod(j)=e=((W1(j)*Pmin(j))+P_chp(j));

model wellfare /all/;

option solprint=off;
option optcr=0;

solve wellfare using MIP maximizing benefit;

display
Produced.l
benefit.l
W1.l
DemandB
DemandE
SupplyE
CHPprod.l
Supply1P
Supply1E
Supply2P
Supply2E
P_sun.l
P_bat.l
P_chp.l
P_b.l
;

execute_unload 'MarketsCommitments',P_b,benefit,
Produced,CHPprod,P_sun,P_bat;
```

A.3 GAMS Code - Reserve Energy Market 24 Hours

```
set j /1*41/


parameter
DemandE_s(j)
DemandB_s(j)
SupplyE_s(j)
Supply3E_s(j)
Supply2E_s(j)
Supply2P_s(j)
Supply3P_s(j)
SupplyB_s(j)
Respons(j)
;

$GDXIN C:\Users\MyUser\Desktop\MasterThesis\MarketService.gdx
*Demand Energy and bid
$LOAD DemandE_s=P_df
$LOAD DemandB_s=B_d_p

*Battery
$LOAD Supply2E_s=B_2_E
$LOAD Supply2P_s=B_2_P
*CHP
$LOAD Supply3E_s=B_3_E
$LOAD Supply3P_s=B_3_P
*Pmin for each agent
$LOAD Respons=Prespons
$GDXIN
;

Display Supply2E_s, Supply3E_s, Supply2P_s,
Supply3P_s, DemandE_s, DemandB_s,Respons;


Variable
benefit_s total profit
;

binary variable
*Generators offer
W1(j)
U1(j)
```

```
U2(j)

*Startup
UST(j)
;

 positive variable
P_chp_s(j)
P_b_s(j)
produced_s
P_bat_s(j)
P_respons(j)
;

EQUATIONS
obj
const1(j)
*USTEQ
DSB
const3(j)
const2(j)
DemResp(j)
;

*Constrain on Generation for CHP
const1(j)..
P_chp_s(j)=l=Supply3E_s(j);

const3(j)..
P_bat_s(j)=l=Supply2E_s(j);

const2(j)..
P_b_s(j)=l=DemandE_s(j);

DemResp(j)..
P_respons(j)=l=Respons(j);

*Energy balance
DSB..
sum((j),(P_respons(j)+P_chp_s(j)+P_bat_s(j)))
=e=sum((j),P_b_s(j));

*Objective function includes start-up cost
obj..
benefit_s=e=sum((j),DemandB_s(j)
*P_b_s(j))-sum((j),P_respons(j)
```

```
*0.001+((P_bat_s(j)*Supply2P_s(j))
+(P_chp_s(j)*Supply3P_s(j))));


model wellfare /all/;

option solprint=off;
option optcr=0;

solve wellfare using MIP maximizing benefit_s;

display
benefit_s.l
DemandB_s
DemandE_s
Supply2P_s
Supply2E_s
P_bat_s.l
P_chp_s.l
P_b_s.l
P_respons.l
;

execute_unload 'MarketService1',P_b_s,benefit_s,
P_bat_s,P_chp_s,DemandB_s,P_respons;
```

A.4 GAMS Code - Real time Market

```
jhm
set i busses /1*41/;
alias(i,j);
set Head2   Line data table headings / Re, Xe, Ch /;


display i,j

parameter

        P_load(i)
        Q_load(i)
        Pmax(i)    max Pgen at bus i /13 inf,16 1/
        Qmax(i)    max Qgen at bus i /13 inf,16 0.3/
        Pemax(i)
        Ilim(i,j)
        Production(i)
        AvialableReserve(i)
;

scalar

        phi                                        /3.141592654/
        Sbase      base in MVA                     /1/
;


$GDXIN   C:\Users\MyUser\Desktop\MasterThesis\ServiceOPF.gdx
$LOAD P_load=P_load
$LOAD Q_load=Q_load
$LOAD AvialableReserve=AvialableReserve
$LOAD Production=Production
$LOAD Ilim=Ilim
$GDXIN


Table LineData(i,j,Head2)
                  Re            Xe           Ch
1.2        0.0000000     0.0208110      0.00000
1.3        0.0000853     0.0000580      0.00100
1.5        0.0000798     0.0000535      0.00097
3.4        0.0000000     0.0737500      0.00000
5.6        0.0000635     0.0000308      0.00048
5.12       0.0003120     0.0002113      0.00380
```

```
5.41      0.0001306    0.0000580    0.00085
6.7       0.0000000    0.0580000    0.00000
8.9       0.0000000    0.0725000    0.00000
8.17      0.0001252    0.0000844    0.00150
10.11     0.0000000    0.0602500    0.00000
10.41     0.0001868    0.0000825    0.00120
12.13     0.0000145    0.0000010    0.00017
12.16     0.0000172    0.0000118    0.00021
12.17     0.0000227    0.0000154    0.00028
12.18     0.0000281    0.0000190    0.00035
13.14     0.0004762    0.0003229    0.00580
14.15     0.0000000    0.0132430    0.00000
16.19     0.0000281    0.0000190    0.00035
17.31     0.0003746    0.0002540    0.00460
17.33     0.0000907    0.0000617    0.00110
18.22     0.0000000    0.0440000    0.00000
18.23     0.0002549    0.0001732    0.00310
18.35     0.0004535    0.0003075    0.00550
19.20     0.0000000    0.0223170    0.00000
23.24     0.0000000    0.1067500    0.00000
23.25     0.0003401    0.0002304    0.00420
25.26     0.0000000    0.0600000    0.00000
25.27     0.0001868    0.0001270    0.00230
27.28     0.0000000    0.0612500    0.00000
29.30     0.0000000    0.0725000    0.00000
29.35     0.0004653    0.0003156    0.00570
31.32     0.0000000    0.0360000    0.00000
33.34     0.0000000    0.0393750    0.00000
35.36     0.0000000    0.0361930    0.00000
35.38     0.0000118    0.0000082    0.00014
38.39     0.0000363    0.0000109    0.00012
39.40     0.0000000    0.0208000    0.00000
41.21     0.0000000    0.0334360    0.00000

;

Parameter Z(i,j), GG(i,j), BB(i,j), YCL(i);
Parameter G(i,j), B(i,j), Y(i,j), ZI(i,j), Theta(i,j);

LineData(j,i,"Re")$(LineData(i,j,"Re") gt 0.00)
= LineData(i,j,"Re");

LineData(j,i,"Xe")$(LineData(i,j,"Xe") gt 0.00)
= LineData(i,j,"Xe");

LineData(j,i,"Ch")$(LineData(i,j,"Ch") gt 0.00)
```

```
= LineData(i,j,"Ch");

Z(i,j) = (LineData(i,j,"Re"))**2 + (LineData(i,j,"Xe"))**2;
GG(i,j)$(Z(i,j) ne 0.00) = LineData(i,j,"Re")/Z(i,j);

BB(i,j)$(Z(i,j) ne 0.00) = -LineData(i,j,"Xe")/Z(i,j);
BB(j,i)$(Z(i,j) ne 0.00) = -LineData(i,j,"Xe")/Z(i,j);

YCL(i) = sum(j, LineData(i,j,"Ch"));

B(i,i) = sum(j, BB(i,j)) + YCL(i);
G(i,i) = sum(j, GG(i,j));
G(i,j)$(ord(i) ne ord(j)) = -GG(i,j);
B(i,j)$(ord(i) ne ord(j)) = -BB(i,j);

Y(i,j) = sqrt(G(i,j)*G(i,j) + B(i,j)*B(i,j));

ZI(i,j)$(G(i,j) ne 0.00)  = abs(B(i,j))/abs(G(i,j));

Theta(i,j) = arctan(ZI(i,j));
Theta(i,j)$((B(i,j) eq 0) and (G(i,j) gt 0))
= 0.0;

Theta(i,j)$((B(i,j) eq 0) and (G(i,j) lt 0))
= -0.5*phi;

Theta(i,j)$((B(i,j) gt 0) and (G(i,j) gt 0))
= Theta(i,j);

Theta(i,j)$((B(i,j) lt 0) and (G(i,j) gt 0))
=2*phi - Theta(i,j);

Theta(i,j)$((B(i,j) gt 0) and (G(i,j) lt 0))
= phi - Theta(i,j);

Theta(i,j)$((B(i,j) lt 0) and (G(i,j) lt 0))
= phi + Theta(i,j);

Theta(i,j)$((B(i,j) gt 0) and (G(i,j) eq 0))
= 0.5*phi;

Theta(i,j)$((B(i,j) lt 0) and (G(i,j) eq 0))
= -0.5*phi;

Theta(i,j)$((B(i,j) eq 0) and (G(i,j) eq 0)) =
0.0;
```

```
Display Y, Theta,Q_load,P_load,Production,Ilim;




VARIABLES
Q(i)            reactive power generation at bus i
P(i)            active power generation at bus i
Ppeak             bought peak power
V(i)            voltage at bus i
Cost              total system cost
Loss              total system transmission losses
Delta(i)        angle in radians
SOC(i)          state of charge at bus i
Pec(i)          charge power from ess
Ped(i)          discharge power from ess
Load              total active load at hour h
Pflex(i)
Qbatt(i)
ReI(i,j)
ImI(i,j)
Iabs(i,j)

test(i)
OptRes(i)
;


EQUATIONS
LossEq            Total system losses in per unit MW
Equn1(i)        Real power load flow equation
Equn2(i)        Reactive power load flow equation
RI(i,j)
II(i,j)
Itot(i,j)
;


*Loss equation
LossEq..
Loss =e= sum((i),OptRes(i)+Production(i))-sum((i),P_load(i));

*P_load(i)-Pflex(i)
```

```
*Limitations
V.up(i) = 1.05;
V.lo(i) = 0.95;



*Limitations for the Reserve energy
OptRes.up(i)=AvialableReserve(i);
OptRes.lo(i)=0;

*Power flow equations
Equn1(i)..
OptRes(i) + Production(i)
-P_load(i) =e= Sum(j, Y(i,j)
*V(i)*V(j)*Cos(theta(i,j) +
Delta(j) - Delta(i)));

Equn2(i)..
Q(i) - Q_load(i)+ tan(arccos(0.98))
*OptRes(i) =e= -Sum(j, Y(i,j)*V(i)
*V(j)*Sin(theta(i,j) + Delta(j)
- Delta(i)));


*Calculates and limits the current
RI(i,j)..
ReI(i,j) =e= V(j)*Y(i,j)*COS(Theta(i,j)
+Delta(j)) - V(i)*Y(i,j)*COS(Theta(i,j)
+Delta(i)) + V(i)*LineData(i,j,"ch")
*SIN(Delta(i));

II(i,j)..
ImI(i,j) =e= V(j)*Y(i,j)*SIN(Theta(i,j)
+Delta(j)) - V(i)*Y(i,j)*SIN(Theta(i,j)
+Delta(i)) + V(i)*LineData(i,j,"ch")
*COS(Delta(i));

Itot(i,j)..
Iabs(i,j) =e= sqrt(power(ReI(i,j),2) + power(ImI(i,j),2));

*Limitations for the current in the cables
Iabs.up(i,j) = Ilim(i,j);
Iabs.lo(i,j) = -Ilim(i,j);

model OPF /
*all
```

```
losseq
Equn1
Equn2
RI
II
Itot
/;

option nlp=minos;


solve OPF using nLP minimize Loss;


display P_load,OptRes.l,AvialableReserve,V.l,Y,Loss.l,Production
,V.l,Q.l;


execute_unload 'ServiceOPF_f_g',OptRes,Loss;
```