PALESTINE POLYTECHNIC UNIVERSITY **AL-QUDS UNIVERSITY**

Master Program of Renewable Energy and Sustainability

Consumer Load Management Using Forecasting Algorithms

By

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Supervisor

Dr. Radwan Tahboub

August, 2019

	JAMILA	

Joint mAster of Mediterranean Initiatives on renewabLe and sustainAble energy

Palestine Polytechnic University

Deanship of Graduate Studies and Scientific Research

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Thesis submitted in partial fulfillment of the requirements of the degree

Master of Science in Renewable Energy & Sustainability

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In partial fulfillment of the requirements for the degree of Master in Renewable Energy & Sustainability.

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Dedication

I dedicate this work to my family.

Acknowledgement

I would like to express my sincere gratitude to my supervisor Dr. Radwan Tahboub. He continuously provided me with help, encouragement and knowledge.

Thanks are extended to the program coordinator Prof. Sameer Khader for his efforts towards the success of the program. Also many thanks for my colleagues Dr. Fouad Zaro, Dr.Khaled Tamaizi, Dr. Nassim Iqteit and Mrs. Safaa Adi, She gave me a lot of knowledge and answered all my questions.

I would like to thank JAMILA Project-544339-TEMPUS-1-2013-1-IT-TEMPUS-JPCR funded by the European Union, which was administrated by Sapienza University of Rome and partner Universities for their support in launching this program, provided infrastructure and opportunities for scientific visits.

Finally, my ultimate thanks go to the great edifice of science (Palestine Polytechnic University).

Abstract

With the high-growing demands of modern life and industry on electricity, and with the very rapid growth of renewable energy generation and distribution technologies rise a need of an integrated platform to manage electricity services in more efficient, reliable and intelligent way. Smart Grid Network (SGN) is one of the creative technologies that controls efficient and intelligent traditional and non-traditional resources of energy with respect to electric power generation, consumption, transmission and distribution. The stability of the distribution grid with fail-over techniques and consumer bill reduction are among the main goals of SGN. However, electricity consumers may input the extra stored electricity that they do not consume into the smart grid for sale to reduce peak-time electricity usage. Time-varying pricing schemes have become a main part of smart grids, by managing both sides from the electricity sold to consumers and the electricity pushed from the consumer. Such SGN's can gather information, such as weather forecasts, storage level and the peak-time. Thus, by using this data, future levels of electricity generation (e.g., the energy from Photovoltaics (PV), which is mainly affected by the weather status) can be predicted with high accuracy.

SGN needs to exchange the information between the consumers and the power supply companies. Smart meters are considered as SGN consumer device and will be suggested to be an Internet of Things (IoT) device to be used to record consumption of electric energy in intervals of an hour or less and send that information back to the company in a timely fashion for monitoring, controlling or billing purposes. Through this thesis, a load forecasting model will be presented, in which more than one source of energy is combined with a local grid control system. This model aims to estimate the electrical load of the consumers based on their previous readings. To achieve this prediction, A time series model and stochastic model were applied with a live sample of load profile data. This data was not used previously by any researcher.

Different case studies has been run in order to ensure that the proposed model give the expected results, and investigating the results in different months during the year. To perform such a study, the analysis of the collected data transferred will be experimented and presented so as to minimize the load at the peak time by comparing the expected load level using the Markov Decision Process (MDP) algorithm and the Auto-Regressive Moving Average (ARMA) algorithm. Conclusions show that using the ARMA algorithm give an error percent of 3.7% for one day ahead forecasting. While for one day ahead forecasting, the MDP algorithm gives a range of readings according to the load consumption group.

إدارة الحمل للمستهلك باستخدام خوارزميات التنبؤ

اعداد: رأفت كريم الجنيدي

الملخص:

مع زيادة الطلب على الكهرباء، ومع النمو السريع في قطاع توليد الطاقة المتجددة وتقنيات توزيعها، تبرز الحاجة إلى نظام متكامل لإدارة خدمات الكهرباء بطريقة أكثر كفاءة وموثوقية وذكاء. الشبكة الذكية Smart Grid Network (SGN) هي واحدة من التقنيات الإبداعية التي تتحكم في موارد الطاقة التقليدية وغير التقليدية بفعالية، حيث انها تقوم بمتابعه عمليات توليد الطاقة الكهربائية واستهلاكها ونقلها وتوزيعها. من بين الأهداف الرئيسية للشبكة الذكية هو الحفاظ على استمراريه الخدمة مع ضمان خفض فاتورة المستهلك. يتم ذلك بالسماح للمستهلكين إدخال الكهرباء الإضافية المخزنة او المولدة من قبلهم في الشبكة الذكية للبيع وذلك لتقليل استخدام الكهرباء في وقت الذروة. وبالتالي أصبحت التسعير المتغيرة مع الوقت للاستهلاك جزءًا رئيسيًا من الشبكات الذكية، من خلال إدارة كلا الجانبين من الكهرباء المباعة للمستهلكين والكهرباء المضخوخة للشبكة من المستهلك. يمكن للشبكة الذكية جمع المعلومات، مثل توقعات الطقس ومستوى التخزين ووقت الذروة. حيث يتم استخدام هذه البيانات التنبؤ بمستويات الاستهلاك او الانتاج في المستقبل (مثل الطاقة الكهروضوئية، والتي تتأثر بشكل رئيسي بحالة الطقس) بدقة عالية. تعتبر تقنية انترنت الاشياء Internet of Things "IoT" الجديدة والتي تجعل الأشياء قابلة للبرمجة والتحكم فيها بواسطة شبكات الحاسب والتي يمكن استخدامها لجمع البيانات من الشبكة ومعالجتها وأداء المهام وفقًا للنتائج.

توضح هذه الأطروحة كيف يمكن للمستهلكين الاستفادة من المعلومات المتوفر لأحمالهم السابقة في التنبؤ بالحمل لمده معينه وذلك باستخدام خوارزميات مقترحة من أجل الحصول على أقصى قدر من الفائدة، من خلال النظر في الأسعار المتغيرة للسوق بالإضافة الى سلوك المستهلك واستخدامها في التنبؤ للأحمال المستقبلية القريبة. لإجراء مثل هذه الدراسة سيتم تجربة تحليل البيانات التي تم جمعها وتقديمها من أجل تقليل الاستهلاك خلال وقت الذروة من خلال مقارنة مستوى الحمل المتوقع باستخدام خوارزمية MDP وخوارزمية ARMA. تُظهر الاستنتاجات أن استخدام خوارزمية ARMA يعطي خطأ بنسبة3.7٪ للتنبؤ قبل يوم واحد. بينما على المدى القصير، ستقدم خوارزمية MDP تقديرا للحمل وفقًا لمجموعة استهلاك الحمل.

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Abbreviations

ACF	**A**uto-**C**orrelation **F**unction
ACC	**A**uto-**C**orrelation **C**oefficient
ANN	**A**rtificial **N**eural **N**etworks
ARMA	**A**uto-**R**egressive **M**oving **A**verage
ARIMA	**A**uto-**R**egressive **I**ntegrated **M**oving **A**verage
ARMAX	**A**uto-**R**egressive **I**ntegrated **M**oving **A**verage with e**X**ogenous inputs
BDAP	**B**ig **D**ata **A**nalytic **P**latform
BIC	**B**ayesian **I**nformation **C**riterion
CoEC	**C**ost **o**f **E**nergy **C**onsumption
DMS	**D**emand-**S**ide **M**anagement
EMS	**E**nergy **M**anagement **S**ystem
GPS	**G**lobal **P**ositioning **S**atellite systems
HEMS	**H**ome **E**nergy **M**anagement **S**ystem
HMM	**H**idden **M**arkov **M**odel
ICT	**I**nformation and **C**ommunications **T**echnology
IoT	**I**nternet **o**f **T**hings
IRENA	**I**nternational **R**enewable **E**nergy **A**gency
MDP	**M**arkov **D**ecision **P**rocess
PACC	**P**artial **A**uto-**C**orrelation **C**oefficient
PV	**P**hoto**V**oltaics
PACF	**P**artial **A**uto-**C**orrelation **F**unction
PENRA	**P**alestinian **E**nergy and **N**atural **R**esources **A**uthority
PMUs	**P**hasor **M**easurement **U**nits
RTP	**R**eal **T**ime **P**ricing
RTU	**R**emote **T**erminal **U**nits
SCADA	**S**upervisory **C**ontrol **A**nd **D**ata **A**cquisition
SG	**S**mart **G**rid
SGN	**S**mart **G**rid **N**etwok
TW	**T**era**W**att
WAMS	**W**ide **A**rea **M**onitoring **S**ystem

Chapter 1

Introduction

Nowadays, with the high demand of energy consumption rises new visions of energy management and demand response. Smart grid (SG) is a highly automated and integrated power system, Real-Time information flow through network, thus customers can forecast their load consumption and then schedule their behaviors, according to the change of electricity price depending on the history of the load consumption and price profile. Some tools are needed to achieve this forecasting to collect information and analyze it such as Internet of Things (IoT)[8].

IoT is a new technology that takes part in different fields of smart technologies such as Smart Homes, Smart City and Smart Grid Networks (SGN) [9, 10]. These programmable network based devices are used to monitor and control things to perform certain tasks. As SGN and smart city features, IoT devices are used in converting the traditional grid into a smart grid [11]. Monitoring and managing grids in an automated way are the main goals of IoT devices in smart grids. Secure data transmission is needed in this grid; however, hacking the data across the network will affect the work and may cause damage in the grid. The power grid moves the generated electricity from power plants to consumers. Such grids are connected for commercial purposes and more reliable networks that enhance the management and planning of electricity demand and supply. Depending on the International Renewable Energy Agency (IRENA) report[12], renewable energy generation is rapidly growing worldwide [12]. from 2012 to 2017, Palestine generated about 1, 1, 3, 12, 14, 18 MW respectively from renewable energy resources, mainly from solar energy [12]. This growth is inconsistent with the international growth, where generated power increased from 2012 to 2017 from 1.5 TW to 2.2 TW [12].

The smart grid network is the network that connects to the electricity grid, in order to get information about the power generation, transmission and distribution across all grid operations, using a variety of components [8] including the Smart meter. This can be

an IoT device that records power consumption in a specific time period and sends that information back to the utility for monitoring and billing [13]. Such research primarily focuses on developing smarter control centers and SGN, along with security and other similar concerns. For providers, studies primarily focus on time varying pricing schemes so they can get the best price at a specific time (e.g., to reduce peak-time electricity consumption under certain terms and conditions). Support for high peak-time electricity consumption requires a high sunk cost (initial investment) [1].
Demand Side Management (DSM) is one application of SGN[14]. DSM is the process of modifying the energy consumption on the demand side, typically the consumer grid, in ordering to improve the performance of SGN, thus reducing the peak demand.[14].

Nowadays, customers not only consume electricity, they also convert energy from green resources, such as solar and wind energy, into electricity for their online usage. They also can store the excesses of their demand for future use or sell it to the providers using smart grid, as shown in figure 1.1, which is designed and reviewed from three PhD instructors at Palestine Polytechnic University. Usually, the smart grid owner sets time-varying prices for the sale of electricity to consumers and the purchase of electricity from consumers to reduce peak-time electricity usage and to encourage consumers to sell electricity during peak times. Consumers decide whether to sell their electricity at specific times based on the current storage status, a time varying electricity retail price, known as real-time pricing (RTP)[15], is one of the solutions which predicts future electricity generation and consumption [1].

Figure 1.1 illustrates the generic integration between the renewable energy resources and other parts to the grid. Regardless of the technology used, a complete energy storage system, for example, can operate in an off-grid mode or be connected to the network ”on-grid mode”. Such system has three main components: storage system, control switching system, and switching and synchronizing system. The design of these components is strongly based on the application of energy storage, which is monitored by the controlling system. The controller will read the level of the storage, put the minimum level for local use, and direct the flow of electricity from and to the storage. According to the state of electricity flow, the controller then activate the needed blocks of the system. For example, if the controlling system ”after applying the forecasting algorithm” decided to charge the storage from the provider grid, the AC/DC changer will be activated in this case. The blue arrows in figure 1.1 illustrate the relationship of data flow between different system parts and the controlling system. Switching and synchronizing system used here to match the speed and frequency of the power source to a running network.An AC generator can only deliver power to an electrical grid if it is operating at the same frequency as the grid. In this diagram, there is at least three types of generators: PV generators, Wind turbine generator and the provider generator. This

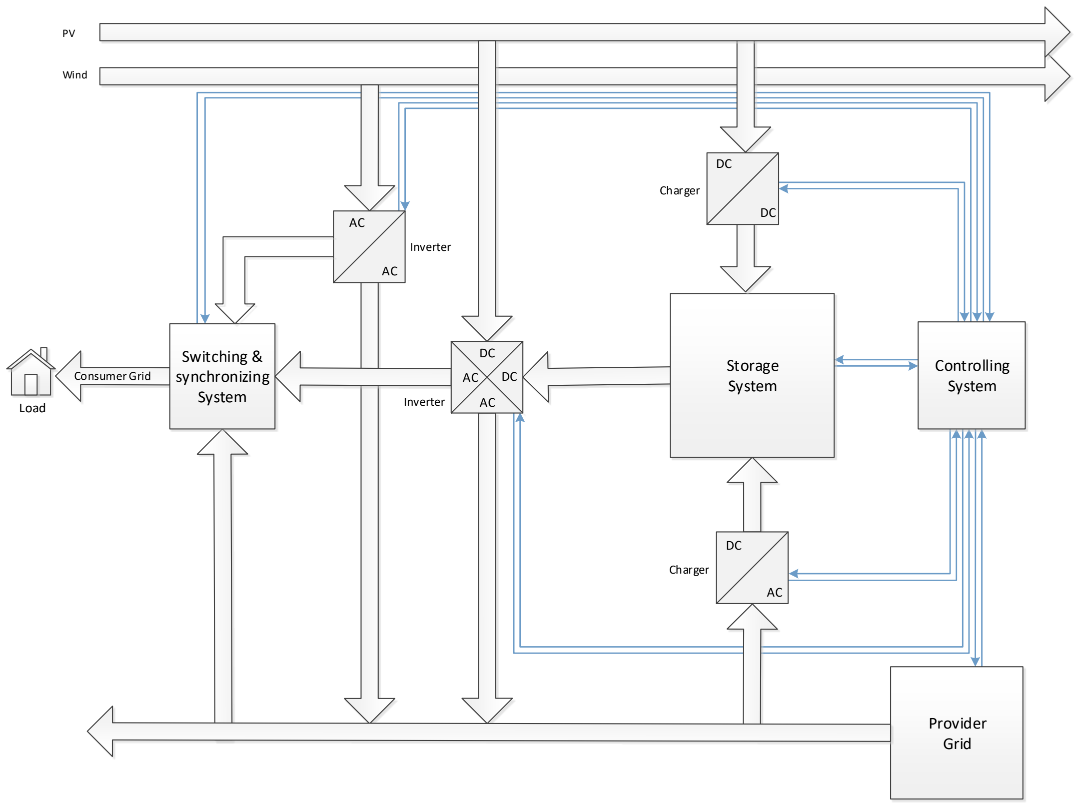

FIGURE 1.1: General DSM Block Diagram

diversity of electricity sources with a storage system, ensures the greatest continuity and availability in the supply of electricity to the consumer. with the applying of forecasting algorithm, it also will reduce consumption bill based on the power profile of the consumer and the statues of the electricity cost from the provider.

SGN with RTP aims to help customers decide when to sell their generated electricity, when to purchase from the grid and at exactly what amount. Smart meters and in-home display units aim to help customers in reducing their Cost of Energy Consumption (CoEC) [15] and control their appliances on a regular basis, also the demands for production services are shifting from the high response and highly efficiency to the safety and high reliability [16].

1.1 Thesis objective

By using several types of energy resources, like natural gas and renewable energy, new challenges of a sustainable energy future appears highlighted by a recent surge of interest in alternative energy resources, including wind, solar, bio-fuel and geothermal energy.

SGN is one of the new applications in which Information and Communications Technology (ICT) is applied to provide consumers with electricity in a more intelligent, stable and efficient manner, thus attracting increasing attention [1].

The objective of this study is to enhance the transformation of the consumer's information to the SGN, thus maintain a reliable and secure infrastructure that can support the future load growth and achieve the characteristics of a smart grid. A time series analysis forecasting algorithms will be used in this study, such as Auto-Regressive Integrated Moving Average (ARIMA) model and compare the results with a stochastic model like Markov decision process (MDP), in order to deploy a smart, stable and cost effective grid. Time series forecasting models are used to predict future values based on previous values[17]. Stochastic models refers to the sequence of random variables [1], in order to describe the behavior of the systems that follow a chain of linked events, where the following events depend only on the current state of the system. The forecasting model is used as a tool to help improve consumers behaviors with the defined objective of enhance the consumers benefit. The dynamic programming and branch-and-bound algorithm design paradigms are applied to reduce the computational complexity. The proposed management scheme can be implemented in each consumers energy generation system to promote better smart grid utilization and attract consumer investment in new energy generation systems [1].

1.2 Thesis motivation

Smart Grid is a new term, that expounds on many meanings of Smart. Smart generation, includes renewable energy integration. In transmission part, smart transmission networks will plan to enhance situational awareness in a secure fashion, like promoting the best design for the customer to purchase from or to the grid. Sending information to the management system, demand response, micro-grid and load balancing can achieve distribution in a smart way [1]. For the end-user, smart metering and smart appliances are the main devices, which will be an IoT device that needs to be part of the SGN. With such devices, customers can participate by taking the decisions of routing data through the grid and receiving RTP from companies.

With this motivation, It is aimed to develop a mathematical model using ARIMA to understand how to get the best offer from the SGN with a resalable and stable service.

1.3 Contributions

Overall, the contributions of this thesis are as follows:

- To help predict future levels of electricity consumption using consumer power profile with sensors like weather sensors and consumer's behavior, that are attached into the smart grid system.
- To schedule consumers behaviors using forecasting models in order to enhance their benefits- such models help the consumers take decision that reduces their CoEC [15].
- To compare between the forecasted results that are generated from the forecasting models, and get the percentage error for each.

1.4 Research methodology

This thesis proposes a method for improving the performance of SGN. To achieve this goal, a code of forecasting models will be run using a real load data. The consumer can send and receive his information among SGN using different technologies like smart meter. Load consumption history and other variables like storage level and consumption price index is one of the data that are transited along the SGN. The forecasting models can help the consumers of taking the decision about which energy source that make the best price effort with maximum benefit of local resources.
After collect data from providers, forecasting models will be applied with this data as input data. Time series forecasting models like the ARIMA model, and Discrete Stochastic models like the MDP will be selected to perform the prediction process. The results from the two models will be compared with the real data in order to get the resolution of each one. Then using the same results to compare between the ARIMA model and the MDP model, and put suggestions for the providers at Palestine to get benefits from such studies.

1.5 Summary and rod map

This chapter introduce an introduction about SGN. Time-varying price is one of the strategies that are used to reduce the peak time. In this thesis, a forecasting models will be applied to predict the future load of the consumer using load profile data. Six chapters will take part in this thesis to present my study. Chapter one give an introduction about the case study. Chapter two present a general background about the SGN and the forecasting models. Literature review about related studies will be displayed in chapter three. The next chapter will present the methodology of this thesis. The last two chapters will give the thesis experiments, results and the conclusions of the proposed scheme and the future works.

Chapter 2

Background

In this part, an overview of the electricity system concept for the smart grid system will be presented, in which electricity consumers can also participate in generating electricity. It first introduces the pricing model designed by the electricity plants, including the prices at which they sell electricity to consumers and the prices at which they purchase electricity for consumers. The assumptions made will be concerning electricity and consumers electricity generation and consumption, which will be mentioned at the end of this section.

2.1 Smart grid

Due to the new challenges of the power systems field and the size of investment that has been made in the field, significant changes appear to solve the new challenges[18]. In this study, we design a model for an electrical system of a networked smart grid, in which most buildings have the ability to converting solar energy or energy from other green sources, such as wind, into electricity. Capacities such as batteries for electricity storage are added to the electricity generating system in order to allow the generated electricity to be stored in self-use or sale. A monopoly market is considered, in which there is only one electricity plant.

Referring to figure 2.1, the system has a single plant that generates electricity[2], which is transmitted via the smart grid. They divide users into three categories: always-insufficient consumers such as large factories (who demand more electricity than they can generate), always-sufficient consumers (who always generate more electricity than their demands) like small house, and other consumers (such as certain residential consumers). Each consumer has a solar generator in order to generate electricity, an electrical storage

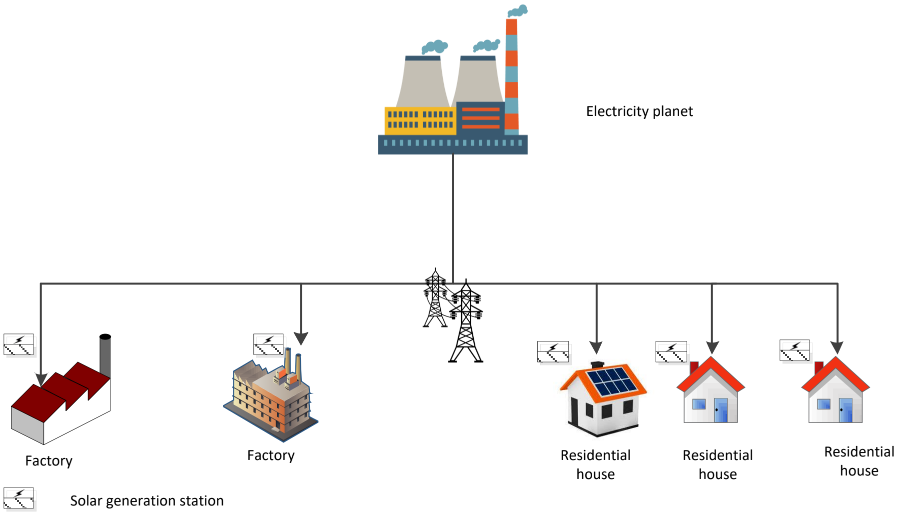

FIGURE 2.1: Illustrations of an electricity system for the smart world[1]

unit, where the additional generated electricity can be stored for future use or for sale to the grid [1].

In order to model the smart grid, several renewable energy sources can be used, such as solar PV, wind and biomass energy. The designed system that considers the different behaviors of customer consumption analyzes the consumption at two different month's in Norway, April and July. In April 2018 the average temperature recorded was about 24 degrees Celsius, while in July, the average temperature recorded was about 30 degrees Celsius, with average consumption parameters values. The Matlab application tool used to generate an hour by hour load profile for a load in Norway[6][19], which will be the input for the algorithms.
The converter consists of a rectifier and an inverter. A battery is used as a storage system in order to store the extra energy generated by the consumer (when the system is considered in off grid phase by the controller) and supplies it back to the grid when needed, according the system's decisions as it mentioned in figure 1.1. Such part tacks the main parts of the consumer grid at the smart grid, Figure 2.2 shows the block diagram of the smart grid where monitoring and energy storage are used for design.

Unlike the related studies discussed above, this study considers a system in collecting

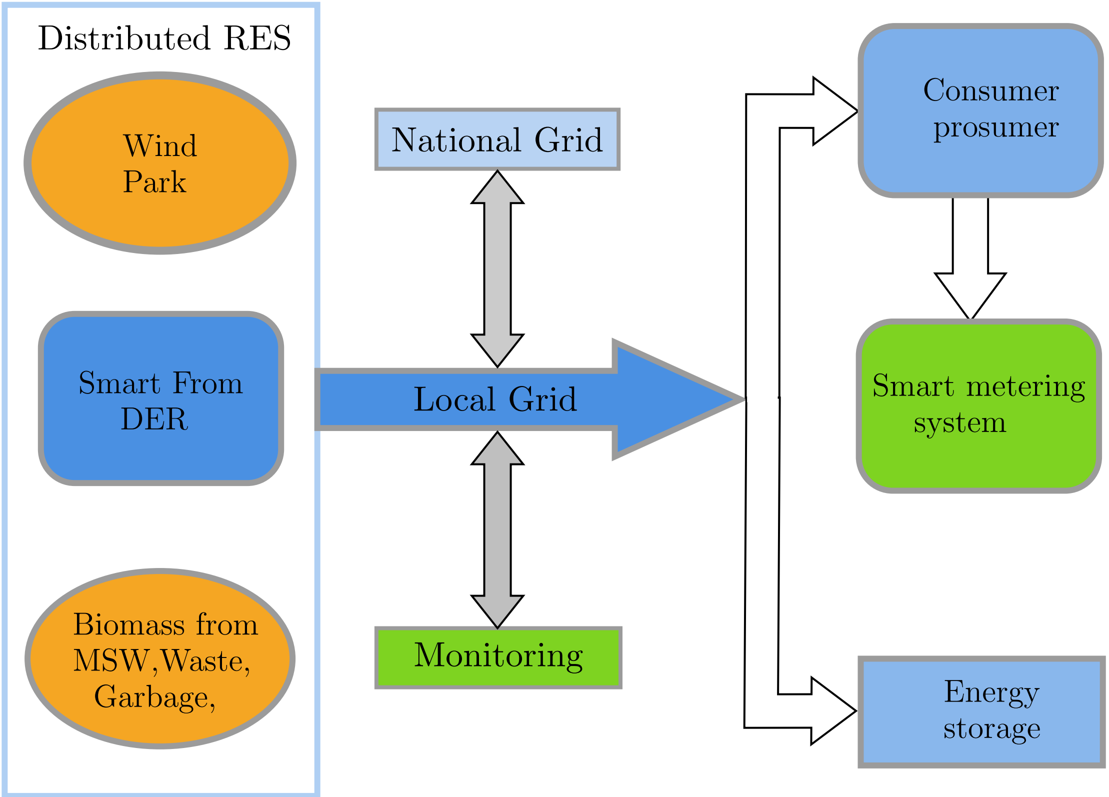

FIGURE 2.2: Block diagram of Smart Grid

data from IoT devices (such as a temperature sensor) which will be used to predict future levels of electricity generation in a networked smart grid. This model is considered as a tool that improves consumer behavior, with the objective of maximizing their overall benefit by predicting the potential fluctuations in users' electricity consumption [1].

2.2 Forecasting models

Forecasting models are a frameworks used to predict future events by using past data[20]. There are many models available to use. in this thesis, a time series analysis forecasting models and Discrete stochastic models were chosen. The test is based on the nature of the data, since the data used is not based on a mathematical equation, it were taken from readings for consumption in a given load. They are random and unstable, and therefore need prediction algorithms that take advantage of previous readings to form a certain format of equations[21].

2.2.1 Time series analysis forecasting models

Time series analysis is a set of ordered observations on a quantitative characteristic of phenomena based on a set of measured time series data[22]. It is mainly a statistical method that deals with time series data, which is data set in a series of intervals. Time series analysis aims to forecast future values based on existing series. Its used for storage, show and analysis of data across a wide range of different domains[22]. There are many possible fields of research based on time series, such as engineering, economics and load prediction.

For one day load forecasting, time series assumes that the load data has inherent rules, such as hourly difference, to forecast 24 hour load[18].

2.2.1.1 ARMA models

Auto-Regressive Moving Average (ARMA) models are used to predict future data in a time series, which is in time domain finite parameter models[17]. ARMA consists of two parts; Auto-Regression model (AR model) and Moving Average model (MA model). AR models are an illustration of a type of random process, used to describe certain time-varying processes in different fields such as signal processing, depending linearly on the previous values[18]. The AR(p) model is defined as [23]:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \tag{2.1}$$

Where $\varphi_1, .., \varphi_p$ are parameters that can help in defining or classifying a particular system, c is a constant, and ε_t is the random variable for white noise. Moving-average models (or process[17]) of order q MA(q) are an extension of the white noise process, by trying to capture the shock effects observed such as noise[24]. The MA model is defined as [23]:

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{2.2}$$

Where $\theta_1, .., \theta_q$ are parameters, μ is the expectation of X_t, μ often assumed to equal 0 [24].

ARMA(p,q) contains the AR(p) and MA(q) models, The ARMA model is defined as [23]:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{2.3}$$

2.2.1.2 ARIMA models

Auto-Regressive Integrated Moving Average model ARIMA is used to predict annual and hourly electricity consumption. In this thesis it will predict electricity consumption for an hourly load using ARIMA models, as shown below [25]:

$$\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \tag{2.4}$$

Where L is the lag operator (or back-shift operator "B") which operates as the AR coefficients[26], α_i are the parameters of the AR part of the model, θ_i are the parameters of the MA part and the ε_t are white noise terms.

Figure 2.3 shows the process of ARIMA modelling.In the identification part, previous data are often non-stationary, while the covariance changes over time. To make the time series stationary, data transformation is often used. To determine whether the series is stationary or not, The Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) are used to identify the appropriate parameters, which also examines the white noise acceptability until a fitting model is selected.

2.2.1.3 ARMAX models

As ARMAX model maintains simplicity as the conventional ARIMA model, ARMAX is more general and flexible than the ARIMA model. It will improve the forecast accuracy of power consumption over the ARIMA model[26].

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{b} \eta_i d_{t-i} \tag{2.5}$$

where b exogenous input term and η_1,...,η_b are the exogenous (d_t) input parameter .

2.2.2 Discrete stochastic models

Stochastic process is a set of points in time that are associated with or recorded by a set of numbers. These points are randomly changing over time, such as fuel minimization

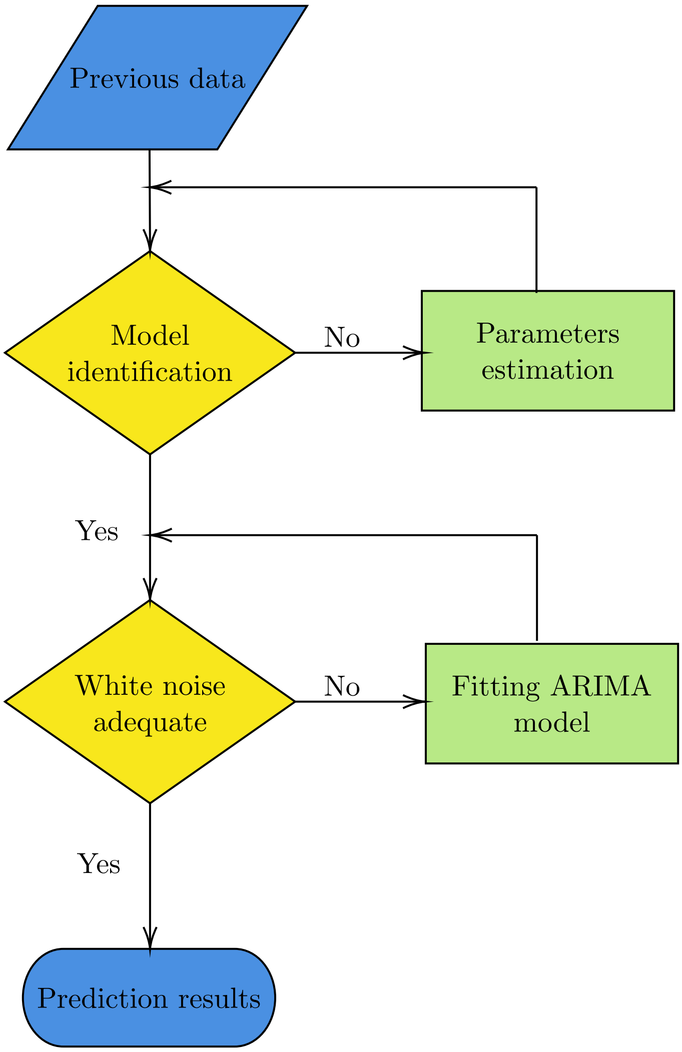

FIGURE 2.3: ARIMA flowchart

for diesel generators [27]. Discrete-time Markov chains is an effective model in dealing with complex problems that have uncertainty.

2.2.2.1 MDP model

Markov chain refers to the sequence of random variables, such process moves through, in order to describe the behavior of the systems that follow a chain of linked events, where the future behaviors depends only on the current state[28].

As shown in Figure Figure 2.4, the possible values of Xi form a countable set S called the state space of the chain. A discrete-time Markov chain is a sequence of random variables (set), S={ s_1, ... ,s_r }. The process starts with one of these variables and moves from

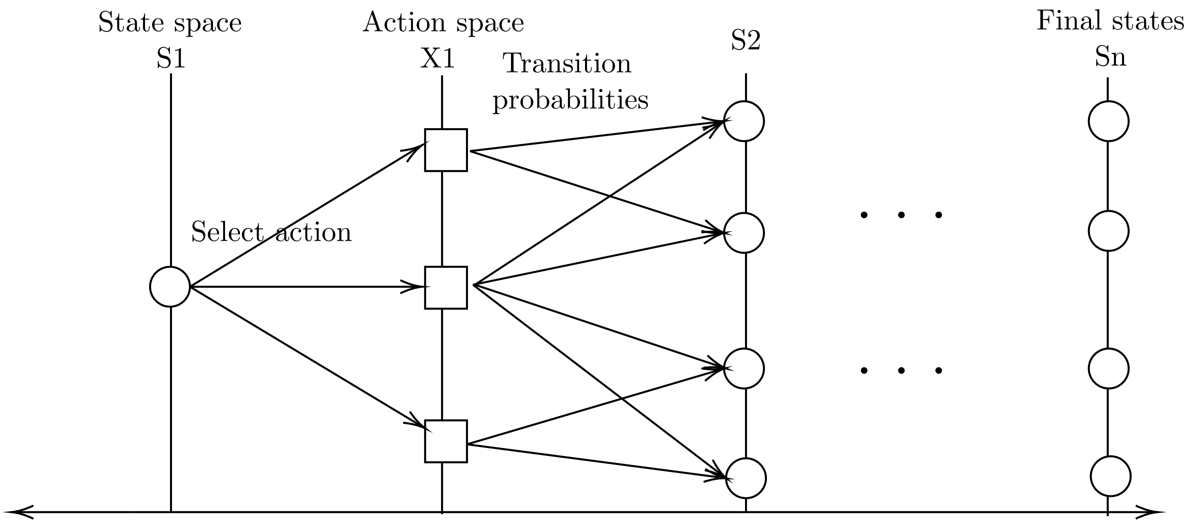

FIGURE 2.4: MDP Illustration[2]

one state to another. If the chain is currently in state s_i, then it moves to state s_j with a probability denoted by transition probabilities p_{ij}. This probability depends only on the present state and does not depend on which state the chain was in before the current state. If a Markov chain has n states, then[29]:

$$p_{ij} = \sum_{k=1}^{n} p_{ik} p_{kj} \tag{2.6}$$

Where p_{ij} is an entry in the transition matrix P.

2.2.2.2 HMM model

Markov models are often used to predict long-term steady-state probabilities of the system with a finite number of states, using inter-state transition probabilities like predicting electricity pool prices[30]. Many models of the main Markov were derived to perform several applications. Hidden Markov Model (HMM) is one of the advanced forms of the Markov model with a hidden system state. The output depends on the internal states. Let $y_i$be the observed process depending on the current state and xi be the input state variables in a standard HMM, then[30]:

$$p(x_0, x_1, ..., x_n, y_1, y_2, ..., y_n) = p(x_0) \prod_{i=1}^{n} p(x_i | x_{i-1}) p(y_{i|x_i}) \tag{2.7}$$

2.3 Summary

Throughoute this chapter, a theoretical background was introduced about SG and several forecasting algorithms that predict the future level of hourly load consumption. In this thesis, time series analysis forecasting models and discrete stochastic model will be proposed using real hourly load consumption and pricing data to compare the results in order to choose the optimal hourly forecasting model.

Daily and hourly data pose a challenge for a different reason, often involving multiple patterns, so we need to use a model that handles such changing on data. If the time series is relatively short so that there is only one type of predictable fluctuation, it is possible to use one of the time series models that was discussed previously (for example, ARIMA model). However, when time series are long enough for some longer periods to become apparent, we need to use other forecasting models like discrete stochastic models.

Chapter 3

Literature review

3.1 Overview

The load forecasting process is a process that depends on load profile. Such forecasting can be applied in SGN, so that it will improve the consumers behaviors specially at the peak-time. Time series forecasting models and discrete stochastic models are used to predict the future level of loads, these models can be run on embedded systems, like IoT devices. Also, IoT's can be used to transfer data such as wind speed and temperature, from different stations and use it in the forecasting process.

3.2 Smart Grid Network "SGN"

In the future of SG, there will be many sources and applications that will be connected to the network, such as distributed generators of renewable energy resources, smart meters and sensors. After integrating these components with the network, the network become intelligent, efficient and more complicated. Data exchange between these components is therefore required, increasing SG's flexibility, scalability and security. The SG system addresses the margin between the energy source and information technology systems. Such information helps to improve grid utilization[31], as well as gathering online information help the grid to be stable during the peak time. By using urgent situations for communication, the efficiency of power distribution will improve[31]. A smart grid will be the next generation of power grid, with a more intelligent, flexible, reliable, self-balancing, and interactive network that enables economic growth, environmental oversight, operational efficiency, energy security, and increased consumer control[31].

By using Markov Decision Process MDP[1] in SG, the results serve as the optimal scheme. Comparing dynamic programming by MDP with the ordinary one (greedy scheme). The MDP executing time decided by the level of the horizon H and the number of cases at a time[1]. As shown in the paper results [1], the results when the time horizon H = 4, the total running time is around 52.1% of the case without using MDP. So applying MDP scheme in SG greatly overcomes the greedy scheme[1].

The authors of this paper[1] introduce for us a scheme with no specific parameters, taking the results and comparing it with other schemes. The experiments were for one day of electricity usage. They divided the day into tow intervals (peak and off-peak time), and gave each part of the day weight, which was used by the algorithm MDP. In the same way, they divided the possible weather conditions into sunny, normal, and rainy, and gave each of them value to be used by MDP.

The next step was to know the amount of electricity that the consumer needed from the plant minus the amount of consumed electricity generated by the consumer.

MDP scheme performs superior to the greedy scheme and somewhat around the optimal scheme when using it for two coming days and different weather situations. This result is because of the inaccurate weather predictions for more than two days.

When the probability of the next two days is sunny, the amount of electricity generated becomes larger for this period, which gives a higher overall benefit. On the other hand, as the prediction accuracy decreases, the performance degrades, which can mislead the decision making process[1].

3.3 Power Management

Multi-objective Power Management on Smart Grid [10] is another paper where the authors describe the power management on smart grid. They start with the Wide Area Monitoring System (WAMS) which can face the new challenges of traditional network-based state-of-the-art data retrieval technology. Its real-time dynamic monitoring utility networks use sensors that can provide synchronized measurements along the Global Positioning Satellite systems (GPS).
They study the power management and present optimization models that will enhance the operations on smart grid. Supervisory Control And Data Acquisition (SCADA) is a computer based system which is like a control Center that manages balancing supply and demand of the power energy, controls and supervises generation by obtaining the power, current and voltage real time data from the Remote Terminal Units (RTU). The

RTU will communicate objects in the physical world with SCADA systems, and provide it to the Energy Management System (EMS) .

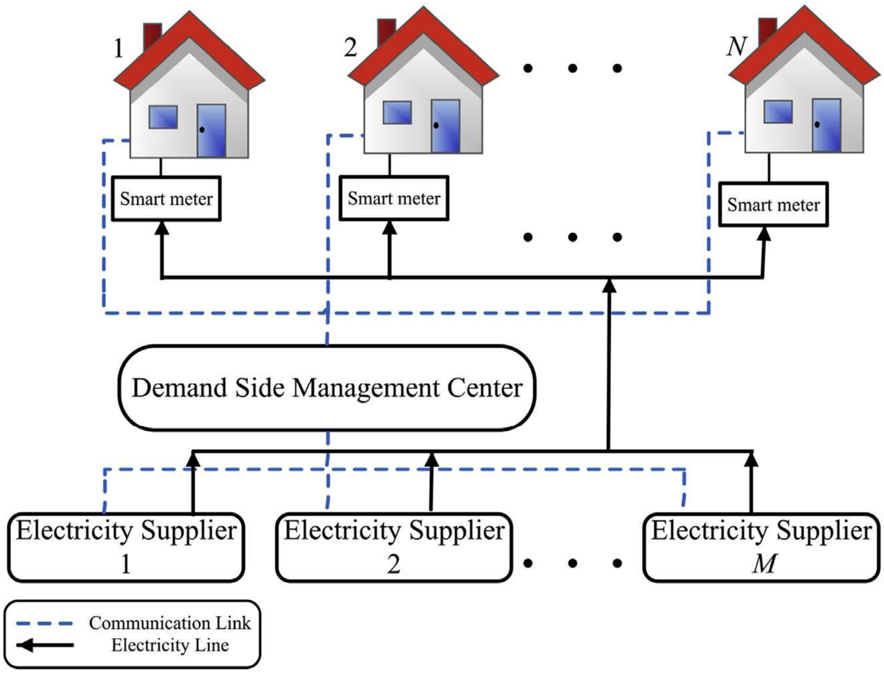

FIGURE 3.1: Diagram of a smart grid system composed of M electricity suppliers, N households with smart meters, DSM center, electricity lines, and communication links. [32]

As it is shown in Figure 3.1 [32], Smart grid system with M power source serving N customers . The group of electricity source and customers is set by M={1, ..., M} and N={1, ..., N} respectively.Day is divided into time slots T, which is divided as T={1, ..., T}, and electricity suppliers are supposed to compete to provide customers with electricity to meet the demand for load all the time slots[32].
Customers are also expecting the price; therefore, they are competing to maximize their reward considering the impact of their work on the value of electricity price[32].

The goal of the power system is to generate power and deliver it to consumers by transmission and distribution networks, in a reliable, efficient, and economical way. So, traditional power plants are located near places where there are large numbers of people.

Table 3.1 show a comparison between traditional and SGN is more flexible in adding new components that help the grid to stay stable. Such grids also can distribute AC-DC and DC-DC. where most of renewable energy source give DC power, it's also can manage the storage components, it's level and place with advanced communication infrastructure and technologies.

Table 3.1: A comparison between traditional and smart power grid[7]

System \Titel	Generation	Transmition	Distribution	Storage
Traditional Grid	Centralized	tough	AC-DC	Traditional low capacity
Smart Grid	Distributed	adaptable	DC-DC \AC-DC	Smart energy storage

In "Energy Management System in Smart Grid using Internet of Things" paper, the authors take the unpredictable accident to the specialists who pay more attention to various issues in energy management. They talk about the changes of connected devices, storage units and the new environmental restrictions. By connecting Phasor Measurement Units (PMUs) to the grid bus and presenting models for the concern of limitation of budgets, This paper proposes a multi-objective optimization model for the PMU placement problem[10].

3.4 Energy Management in Smart Building

Research efforts in this category generally focus on improving energy consumption or reducing the operating cost of smart energy buildings by managing different types of controllable power sources and loads. In "An energy management system for building structures using a multi-agent decision-making control methodology"[33],a description of the structure of a Cyber Enabled Building. The objective of this paper is to minimize the energy cost of a building while satisfying the occupants set lighting and cooling system points using a driven control . A case study used a typical food service centre as an experimental intention has been executed to explain the applicability of this system as a commercial buildings[34]. they proposed an intelligent system to minimize building energy consumption. The system consists of a central coordinator-agent that coordinates the energy dispatch to local controller-agents, and three local controller-agents that use a fuzzy controllers to satisfy different modes of users demands. Within the range of set points for temperature, illumination level, and CO2 concentration given by the users, this system derives the optimal modes to balance power consumption and comfort demands[34].

Another study[35] proposed the EMS for smart homes to get two modes of comfortability: preferred comfort or cost . They conducted a case study with certain energy prices and verified that EMS significantly reduces cost with both solutions.

3.5 Internet of Things

Internet of Things IoT is one of the newer terms that appears in different fields, such as smart homes, smart city and data communication[9]. Its a programmable network based device that can read and send data according to the network, thus performing a certain task[36]. As Smart Grid is one of smart city features [11], adding IoT devices to smart grid can be used for monitoring and managing issues. With such devices, the management of the grid will be more powerful and the cost of automation and management of the grid will be reduced[37]. However, IoT devices can be attached to the grid either on the consumer side or the provider side.

Some previous studies use the term Big Data for the collected data from the different nodes, the paper [3] says that deploying a private cloud, we assure the optimization of resource usage[3]. They use the IoT device as a sensor device so it will collect data and send it to the data store cloud that is suggested to be a third party. The system will decide on either sorting energy or using it. The decision is based on production and storage levels, and the current expected consumption levels [3]. The data gathered will be sent to the cloud using wireless Mesh Sensor Network as shown in figure 3.2.

Home Energy Management System (HEMS) is another system that uses IoT with smart grid in order to maximize the benefit in smart grid [4]. Figure 3.3 shows the purpose of HEMS. The system is used for the emergency based energy by collecting information about demand and output forecast of photo-voltaic [4]. Such systems will encourage consumers to generate more renewable energy and buy back from it.

Four different types of sensors were used in this study; Weather conditions, Electricity consumption, Electricity production and The storage level. This data will be sent to The Big Data Analytic Platform (BDAP) servers controller so that the system will make the appropriate control decisions [3].

The system will gather information like a weather temperature and the storage battery level, and send it to the Community Energy Information System (CEMS), in order to shift in peak and load parameters based on the information[4].

3.6 Forecasting models

Another use of forecasting models is to use various Artificial Neural Networks (ANN) for forecasting hourly solar radiation. It's based on combines ANN with wavelet analysis to forecast total daily solar radiation [26] . ANN models predict solar irradiance based

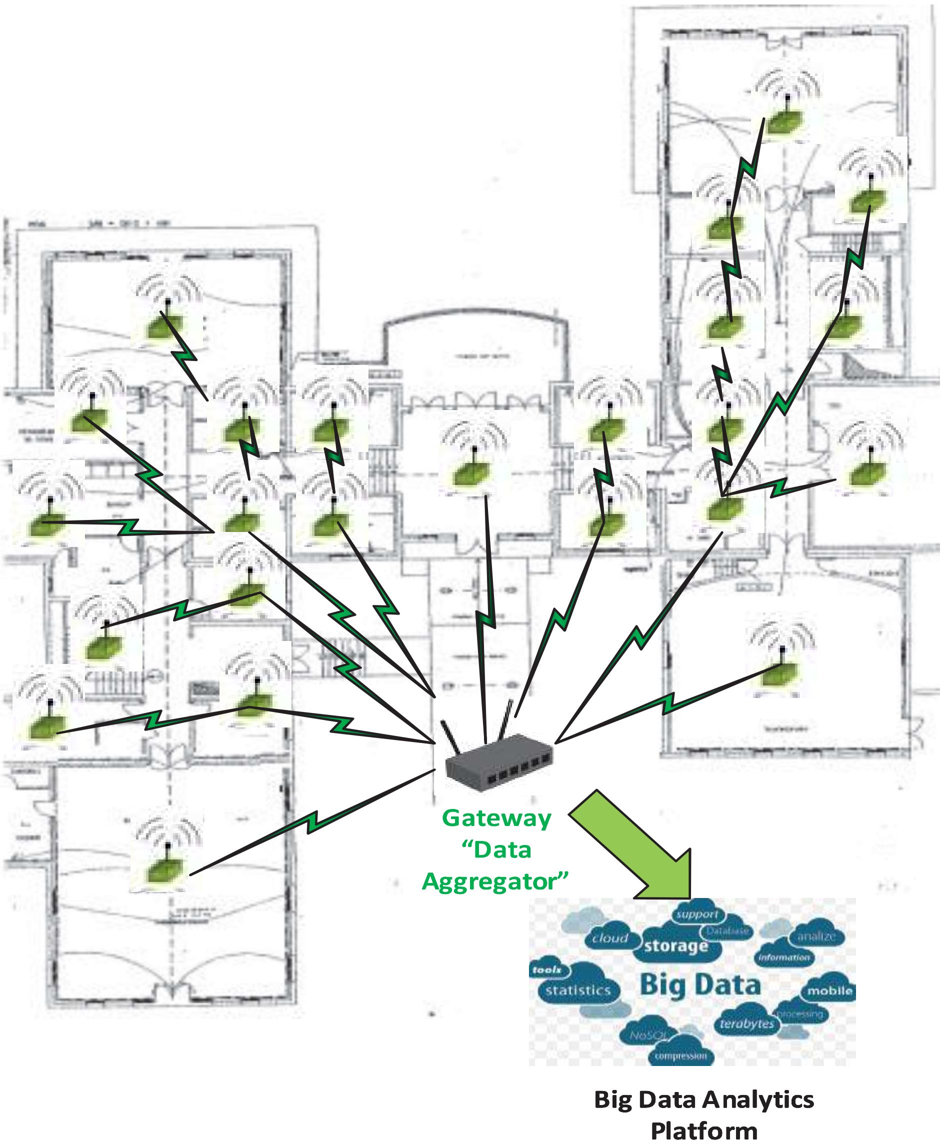

FIGURE 3.2: Wireless Mesh Sensor Network for Data Acquisition [3]

on the previous data and atmospheric data .However, the time series method is a data-driven method . Compared to ANN, the time series models are less complicated than ANN and time series forecasting models contain only a few model parameters[5].

Many models were used for forecasting the power output of a grid connected Photo

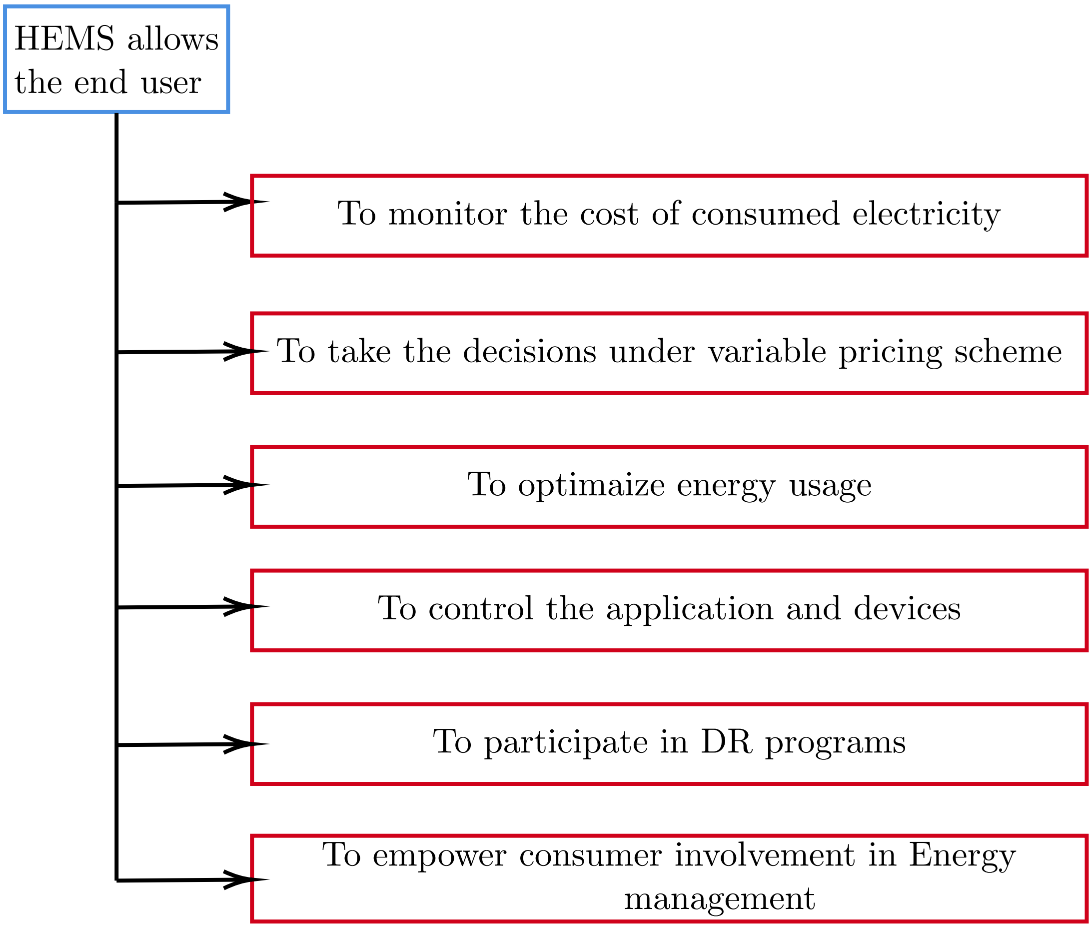

FIGURE 3.3: Purpose of HEMS [4]

Voltaic system (PV), including the ARIMA model. ARIMA is a time series model where AR terms denotes to lags of the differenced series appearing in the forecasting equation, and MA terms are lags of the forecast errors[5].
In order to build an ARIMA model, diagnostic checking is used to calculate the sample Auto-Correlation Coefficient (ACC) and Partial Auto-Correlation Coefficient (PACC), which determines the orders p and q of the ARIMA models, based on the transformed time series[5]. There are many evaluators to estimate ARIMA coefficients.
ARIMA also makes forecasts with a clear sky model[26], which is designed with physical parameters defined for the atmosphere, and a random cloud cover component[26].

The ARMAX model includes useful common parameters in the ARIMA model, where these external co-variables can look at the behavior of the process and thus improve the prediction accuracy of ARIMA models[5].

"An ARMAX model for forecasting the power output of a grid connected photovoltaic system"[5] shows a wide range of time series models to predict a day ahead with an average daily production capacity of 2.1 kW online PV system. Such models are based on moving average techniques, exponential smoothing techniques, ARIMA models, and ARMAX models[5].

An ARMAX model uses some climate variables so that these variables are used when predicting power capacity. which can improve the predictability of the ARIMA model.They derive some climate variables that are easily accessible as external inputs in the ARMAX model[5].

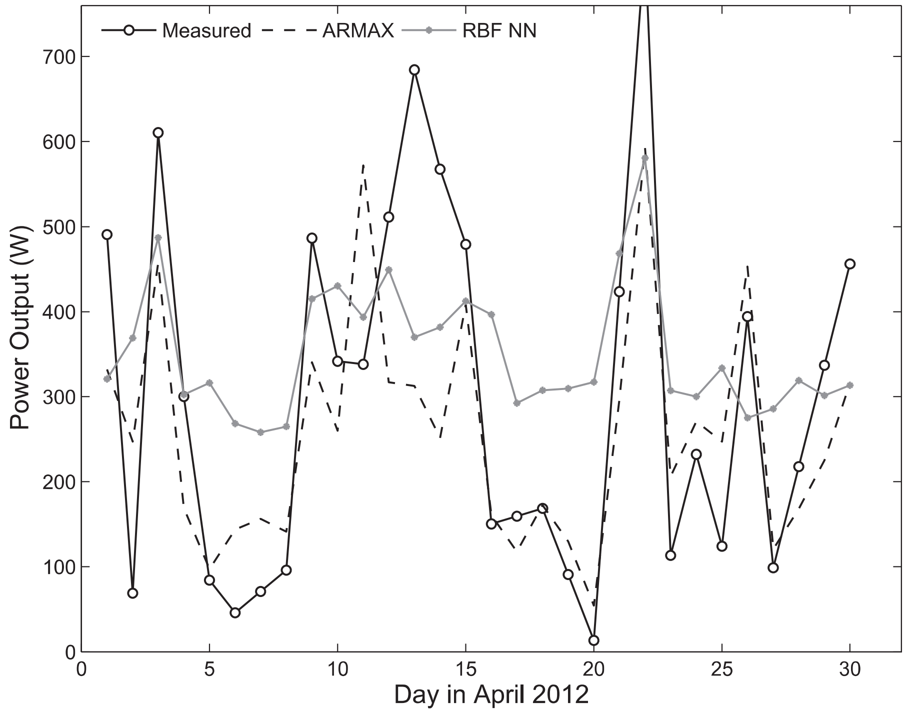

FIGURE 3.4: Comparison of the 1-day ahead forecasts generated based on the RBF network and ARMAX models during April 2012 [5].

Figure 3.4 shows that as a result of the study, the ARMAX model generates the best predictive performance and significantly improves the accuracy of the ARIMA model prediction. ARMAX shows that the information on climate variables, such as average daily temperature, precipitation and other variables are considered to be valuable in predicting PV output power. This reveals that some easily accessible climatic information can be used with ARIMA to enhance the prediction accuracy of time series models[5].

3.7 Summery

This chapter highlighted feedback from the literature review as part of the first stage of the research. The reviews supported the view of how to start forecasting load using forecasting models.

IoT is a new term that can be used as a tool on smart grid, it can collect data from different sensors or sites using wireless network or any other technology, and analyzes it in order to improve the forecasting results. Such features make power generation, delivering and management more flexible, reliable, secure,economical, and sustainable in SG .

Chapter 4

Improving performance

4.1 Introduction

This thesis proposes ARMA and Markov forecasting models to improve the performance of SGN and predict the future level of load consumption hourly, based on previous load consumption records. To achieve this goal, a code of forecasting algorithms can be run over an two months. By using the SGN data transformation techniques, the consumer can send and receive information about the SGN statue, such as grid status and current KWh price index provided from the regulator. Consumption history and other variables like storage level will be monitored by the system and send its information to the regulator. Forecasting models will use this information and then take its decision about the energy source that gives the best effort with maximum benefit of the local resources.

A methodology has been devised, using Matlab codes, to determine the right model that will give a good resolution for load expecting hourly.

4.2 Method

For the implementation and testing, the follow methodologies were decided:

1. Choose the day set from 2018 in order to perform the load prediction.
2. Gather data about hourly cost and load profile for the consumer in 2018.
3. Implement the load forecasting algorithms by using the load profile readings, using Matlab.

4. Compare results with the real data.

5. Give a recommendation about the load forecasting.

4.2.1 Data gathering

The forecasting models, even time series models or discrete stochastic models, are based on previous data. The new data will be driven from the history of data about load consumption, and then compared the results from different models. Thus, after a long search on internet and by connecting electricity market regulations from several areas, Nord Pool Group[38] provided data for Europe's leading power market, offering both day-ahead and real-time market prices to its customers[38]. It also provided an hour by hour price history for the market and give the peak and off peak price for each day.
We can also use this data to predict the load for short or long term, in order to perform that, there are many challenges due to their high volatility and environment dependency, like weather, fuel markets fluctuations and the time of demand[30]. Figure 4.1 show an overview of the main factors that affect the electricity price in market, showing both demand side and supply side[6]. Time of day is one of the factors that determines the price of the electricity as shown in figure 4.1. we can notice clearly in tables 4.1 and 4.2.

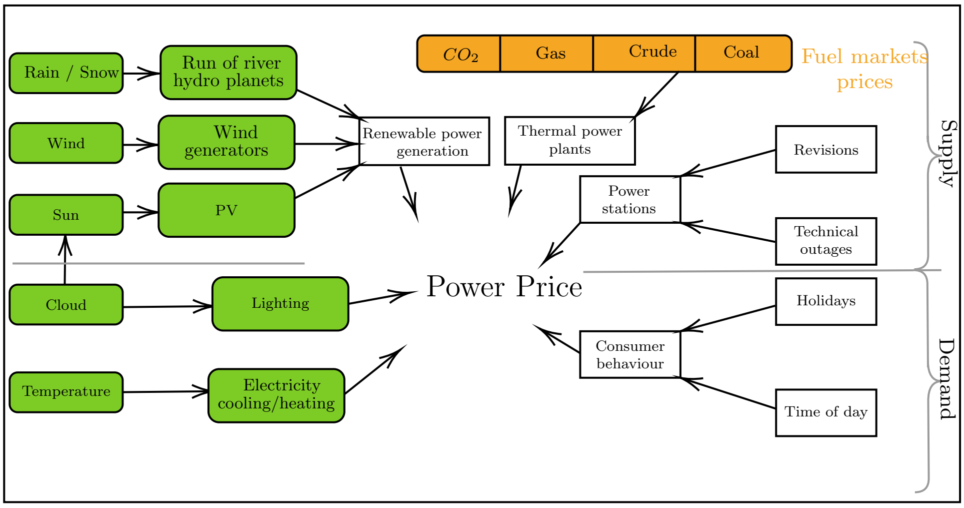

FIGURE 4.1: Factors of electricity price determines [6]

I choose April 2018 and June 2018 as input for the modules, Table 4.1 provide 5 days hour by hour price profile for a medium house as a consumer sample, from the data attached in appendix A.

TABLE 4.1: April hourly prices in EUR/MWh

Time	Price				
	Su	Mo	Tu	We	Th
00-01	39,80	39,38	40,08	39,01	39,13
01-02	39,57	38,67	39,36	38,37	38,50
02-03	39,43	38,43	39,05	38,42	38,49
03-04	39,39	38,33	39,00	38,33	38,95
04-05	39,50	38,61	38,93	38,63	38,90
05-06	39,33	39,27	40,41	39,93	40,25
06-07	39,51	39,96	41,89	42,54	42,25
07-08	39,39	39,62	45,38	48,78	47,03
08-09	39,62	40,33	49,91	58,02	50,21
09-10	39,61	40,56	47,82	51,98	48,78
10-11	39,52	40,63	44,61	46,66	46,40
11-12	39,17	40,32	43,93	44,48	44,26
12-13	38,86	39,91	43,22	42,40	42,76
13-14	38,48	39,52	43,16	41,95	42,20
14-15	38,15	38,97	42,66	41,31	41,20
15-16	38,03	38,81	42,30	41,07	40,96
16-17	38,13	39,08	42,94	41,03	40,98
17-18	38,59	39,53	44,52	41,48	41,03
18-19	39,22	40,11	47,51	42,49	41,39
19-20	39,64	40,88	49,74	42,77	41,95
20-21	40,00	41,09	46,92	44,00	41,92
21-22	39,89	40,92	42,88	42,37	40,95
22-23	39,81	39,96	40,47	40,17	39,93
23-00	39,22	39,22	39,13	38,39	38,09
Peak	38,92	39,89	45,19	44,64	43,51
Off-peak1	39,49	39,03	40,51	40,50	40,44
Off-peak2	39,73	40,30	42,35	41,23	40,22

As it's clear in Table 4.1,for the first five days in April 2018, the price at peak will be the maxim, mostly 08:00 to 09:00 is the first peak time, and 21:00 to 22:00 is the second peak time for the selected load. It seems to be the same peak time of the price system shown in figure 4.2 for June 2018.

Also, It has been taken for the first five days in June 2018 to try the models at summer load. Table 4.2 provide us with 5 days in June hour by hour price profile. The whole month data can be found in appendix A.

Price tables for April and June show that the price of electricity varying during time day. It's ranges from the maximum price at the peak hours, and fall back on the off-peak hours. Off-peak hours are usually when residential loads and businesses use less electricity. It varies depending on location and load type. Mainly off-peak times are at

TABLE 4.2: June hourly prices in EUR/MWh

Time	Price				
	Fr	Sa	Su	mo	Tu
00-01	41,32	42,15	43,39	38,86	42,66
01-02	38,54	40,41	41,59	36,21	41,01
02-03	38,49	39,13	40,04	32,81	39,44
03-04	38,00	38,49	39,33	31,92	39,35
04-05	37,99	38,50	38,43	31,45	39,05
05-06	41,08	38,77	39,25	37,48	41,63
06-07	45,18	40,47	40,18	44,90	45,90
07-08	46,22	42,24	41,39	45,62	46,84
08-09	46,96	43,45	43,08	45,74	46,92
09-10	47,29	44,32	43,57	45,81	47,07
10-11	47,53	43,92	44,03	45,81	47,24
11-12	47,40	43,60	43,89	45,66	47,52
12-13	46,81	43,02	43,89	45,64	47,50
13-14	46,31	42,57	43,46	45,44	47,08
14-15	45,56	42,32	41,62	45,28	46,88
15-16	44,79	42,22	40,97	45,00	46,61
16-17	44,41	42,25	41,32	44,67	46,45
17-18	44,63	43,02	42,58	45,44	46,97
18-19	45,93	43,92	43,57	45,98	47,82
19-20	46,00	44,46	44,50	45,98	48,20
20-21	45,35	43,96	45,11	45,62	47,54
21-22	45,05	43,96	45,29	45,37	47,16
22-23	44,95	43,68	44,94	45,27	47,32
23-00	44,16	42,20	40,66	43,07	44,91
Peak	46,14	43,26	43,04	45,54	47,19
Off-peak1	40,85	40,02	40,45	37,41	41,99
Off-peak2	44,88	43,45	44,00	44,83	46,73

night or weekends.

Variations in demand, weather conditions and transmission capacity contribute to the spot prices wide variation. There is, therefore, great financial risk associated with power trading.

The load forecasting need mainly a load profile for a specific load. Sandels, Widn and Nordstrm intruduse a Matlab application that include an hourly load profile for separate houses[19]. This application generates detailed reference energy profiles for residents of houses, includes load curves that have a similarity with practical load measurements[19].

4.2.2 Data analyses

The hourly electrical load data logged are produced for the 24-hour (one day) period starting at 00:00 AM. The start and end times are a bit random and could be changed according the chosen model system in order to reflect the most efficient time of day to train the model. Processing of previous data is performed to train the models and improve the forecasts. The predictions will focus on the days where load profile manipulation, April and June, were more effective in offsetting costs because of the change of loads behaviors according to the climate variations.

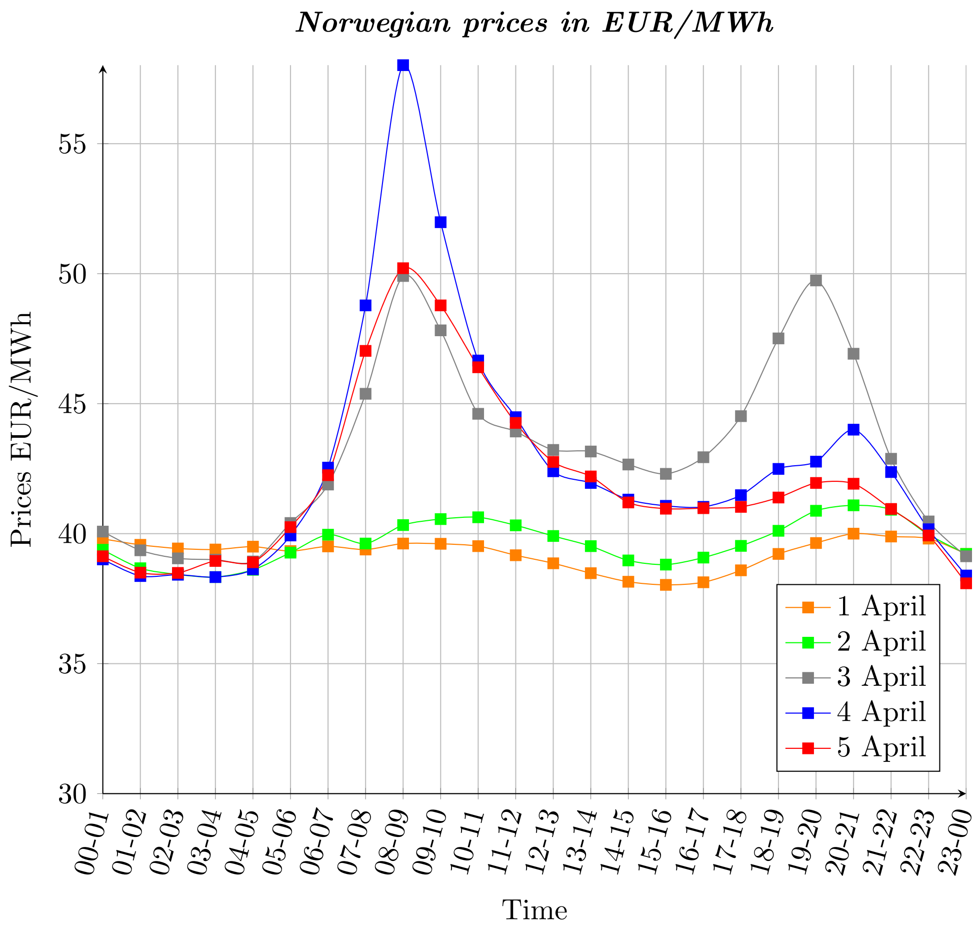

FIGURE 4.2: April 2018 in Norwegian market

Figures 4.2 and 4.3 give us as an overview about the price of electricity, that can be used for price forecasting. Such forecasting depends on alto of parameters like the weather and the time of the day which affect the resolution of the prediction. These parameters were shown in figure 4.1. Figures 4.4 and 4.6 represent the consumer load profile hourly. The full load profiles for both months can be found at appendix. This figure shows that the first peak is from 08:00 AM to 09:00 AM and the second peak 21:00 to 22:00. Figures 4.5 and 4.7 shows the average load consumption for the selected load. The peak time is also as it in the previous figures.

Chapter 2 details the time series models that is applied for 24-hour ahead forecasts. Discrete stochastic models are also used for short term forecasts. Here, the data analyses

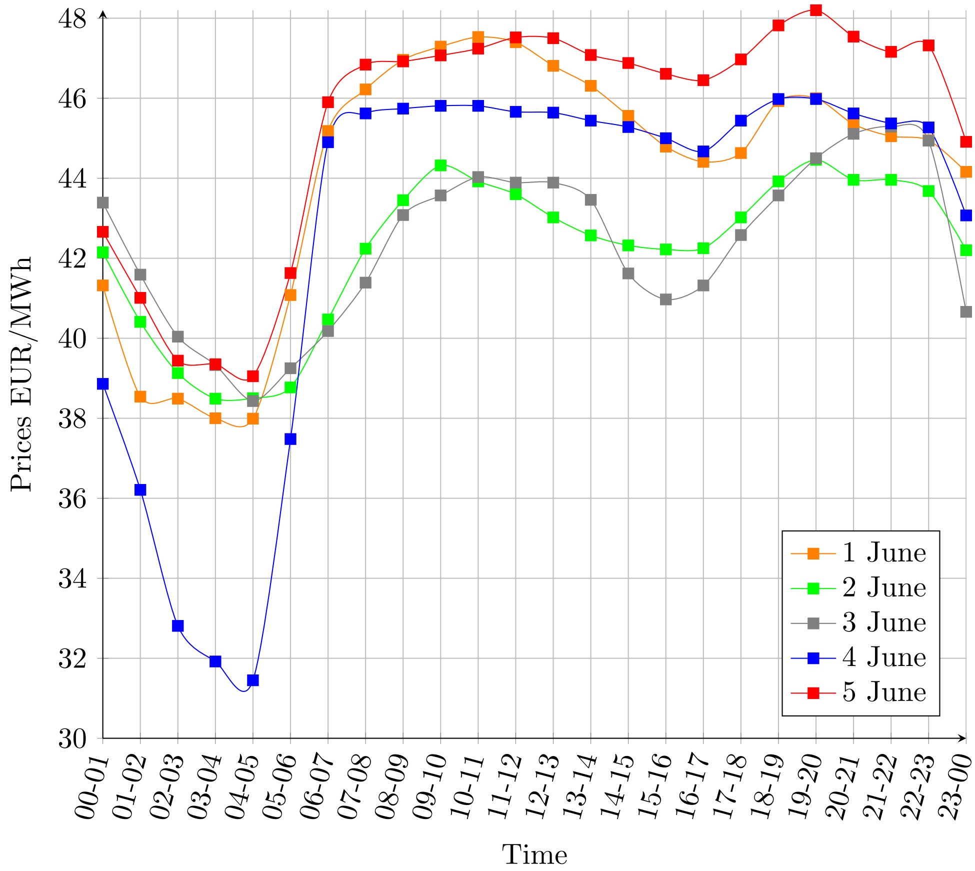

FIGURE 4.3: 5 days June 2018 in Norwegian market

and methods of data management are explained with more detail, as well as the method of testing the models on out-of sample data. Figure 4.8 introduce the load of the first peak (08:00 to 09:00) and the second peak (21:00 to 22:00) in June 2018.Generally, the average load is about 1.2 KWh for the firs peak time and 1.4 KWh for the second peak time. Such data, which is the input of the models, will improve the resolution of the forecasting results.

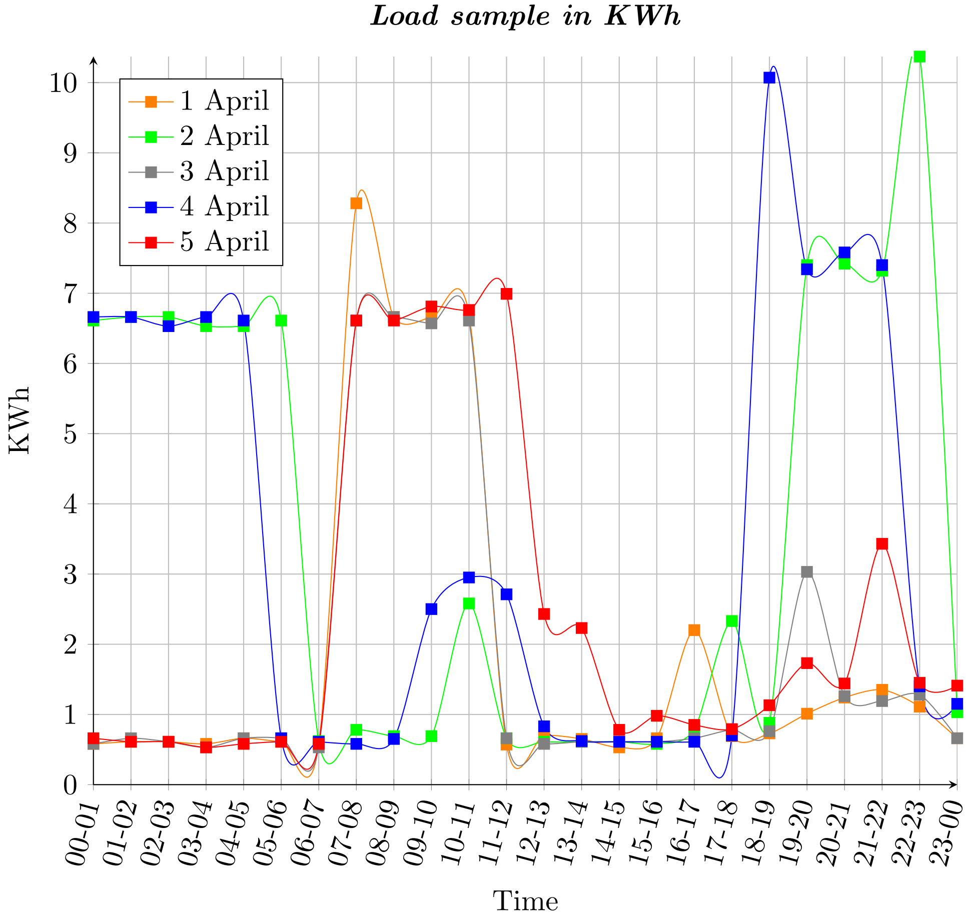

FIGURE 4.4: Comparison between Electricity medium load for 5 days April 2018

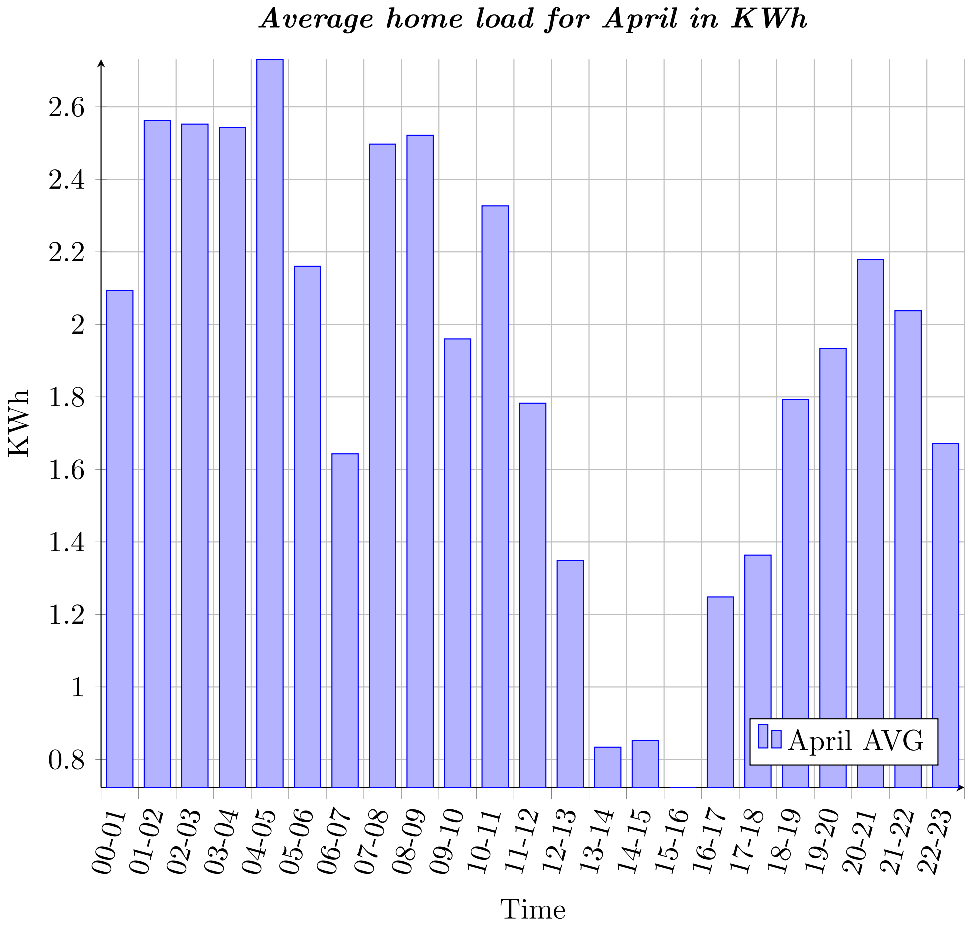

FIGURE 4.5: Electricity medium average load for April 2018

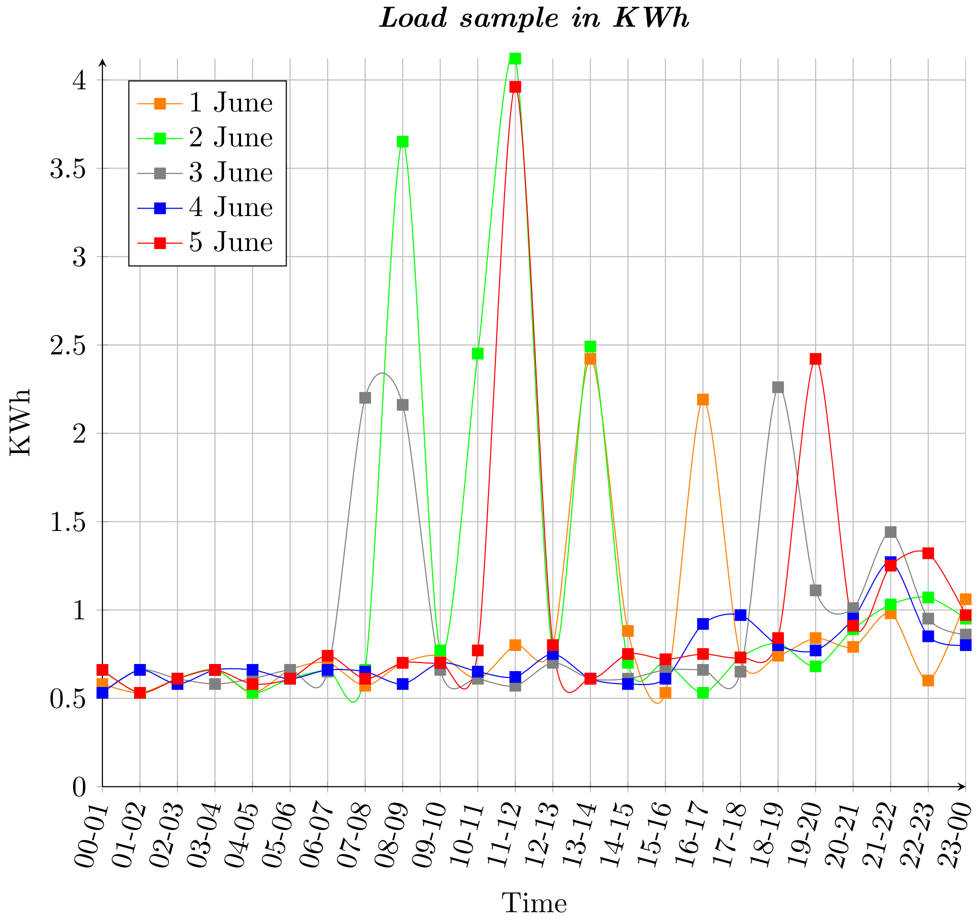

FIGURE 4.6: Comparison between Electricity medium load for 5 days June 2018

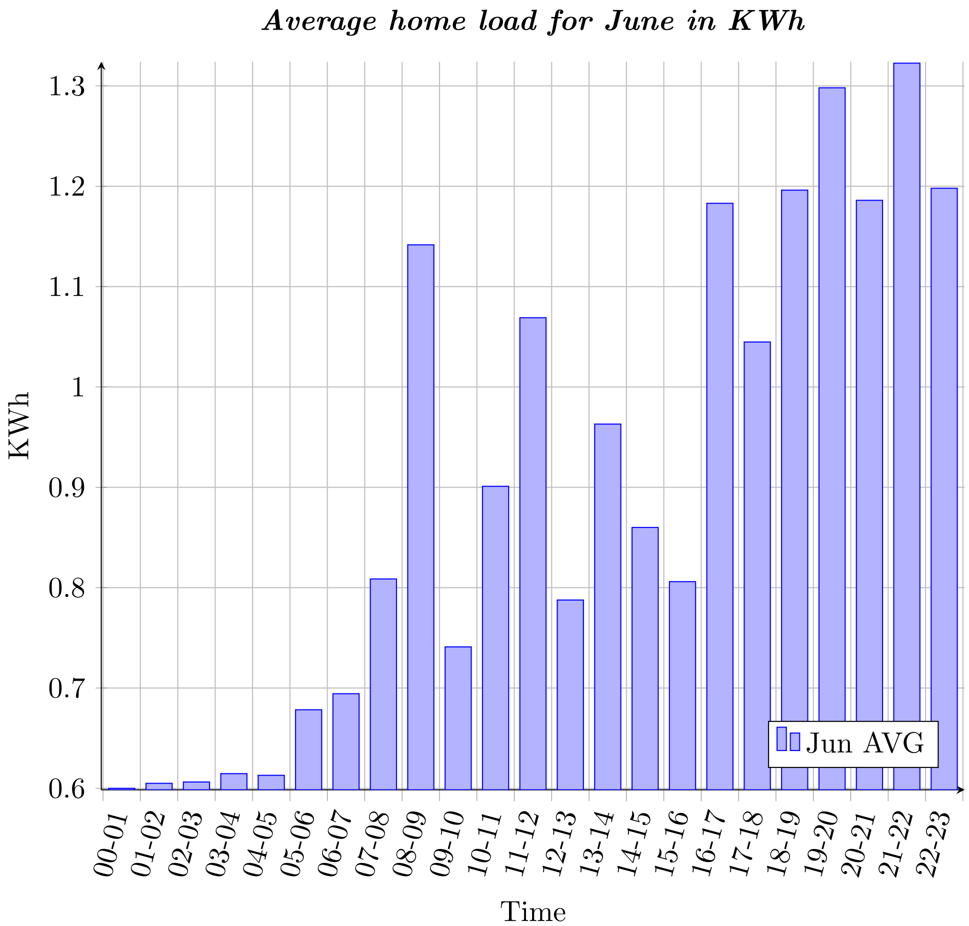

FIGURE 4.7: Electricity medium average load for June 2018

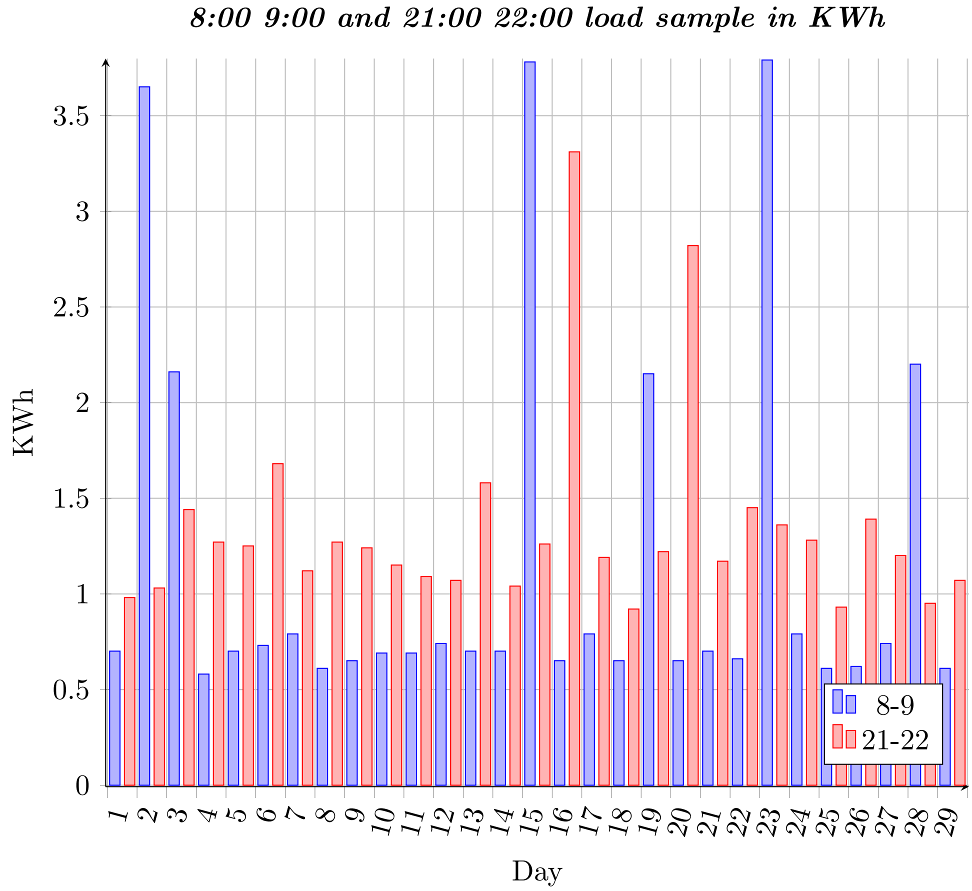

FIGURE 4.8: The load of two peak time clock's over June month

4.2.3 Data preparations

Forecasting process is a history based process, which means that the future predicting loads depends on the previous load consumption for the consumer. Forecasting models use this data and regenerate it to its parameters so that the model can deal with it. Time series modules data preparations and discrete stochastic models data preparations are varying depending on the used model.

4.2.3.1 Time series modules data preparations

Time series modules need the previous data in order to perform forecasting, without a need to group data into categories. ARMA model is referred to as the ARMA(p,q) model; where p is the order of the auto-regressive polynomial and q is the order of the moving average polynomial. To calculate the polynomials p and q, previously, models were identified manually by trying low order models such as ARMA(1,1), ARMA(2,1) and ARMA(1,2). Diagnostic checking used to calculate the sample auto-correlation function (ACf) and partial auto-correlation function (PACf) plots, by comparing the accuracy results and obtaining reduced ARMA model statistics on the data itself and on AR model as first-stage input. In this thesis, ACF and PACF are implemented by Matlab R2018b. They will be used also with ARIMA and ARMAX models.

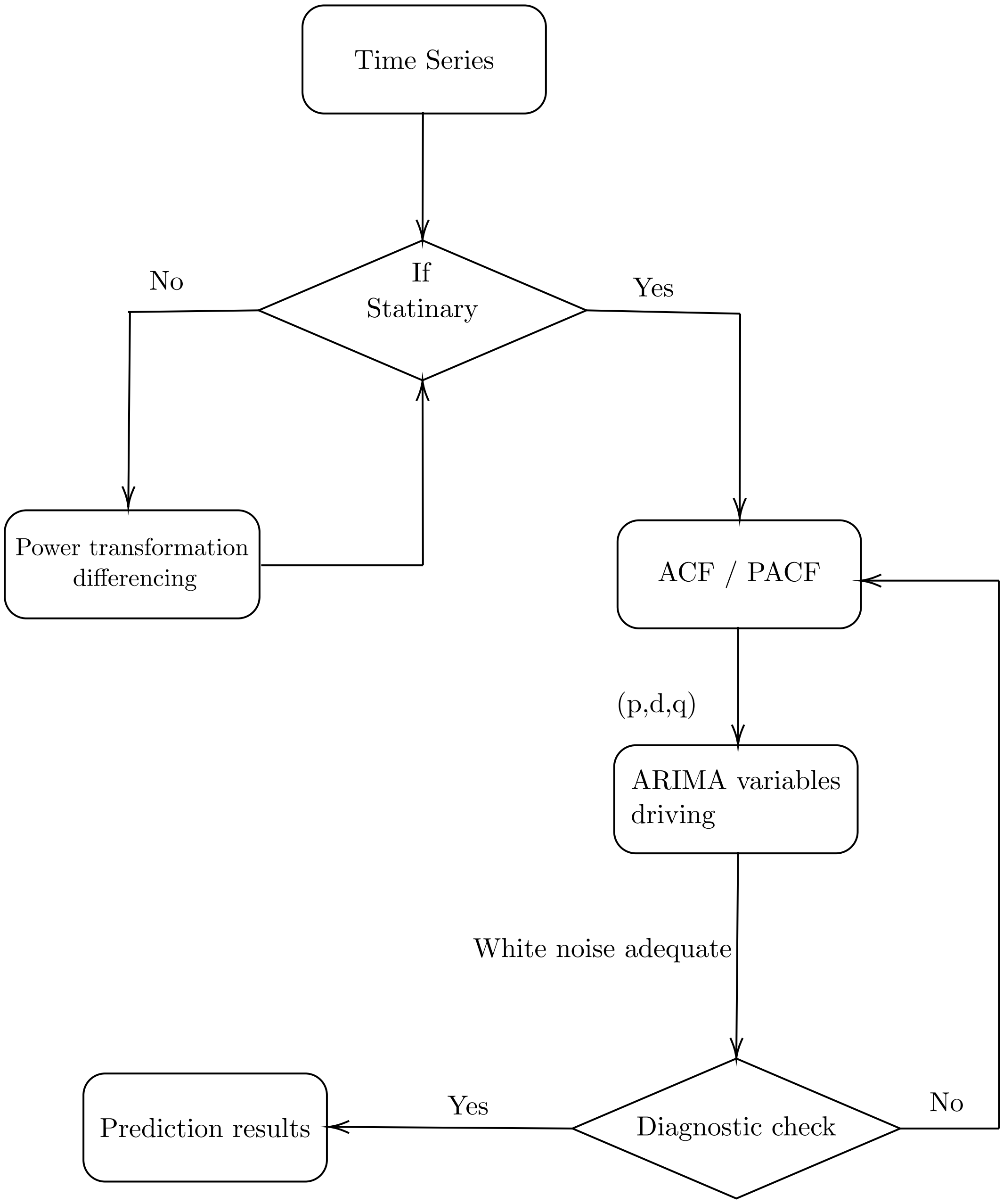

Figure 4.9: Time series algorithm

Figure 4.9 shows the time series algorithm that is implemented by Matlab. The selected models will get load data for April 2018 and June 2018. These data are the main input (previous load data) for the time series model. ARMA, ARIMA and ARMAX coefficients will be estimated using ACF and PACF plots automatically.

Previous data that will be used in these models are the hour by hour load profile for

April and June 2018, which are available at appendices A.1 and A.2. The input of the models will be the load of each hour during 29 days. Usually, the temperature during the month is around the average which is given in table 4.3.

TABLE 4.3: Norway monthly average temperature

Temp. \Month	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
High °C	1	2	6	9	16	20	22	20	16	10	4	-1
Low °C	-7	-7	-3	1	7	11	13	12	7	4	-1	-5

The load forecasting process will be driven hour by hour during 24 hour. The results will be compered with the real load at each hour. We also can produce day by day load forecasting using the average load each day, or forecast the load for the peak time. Getting such statistics can help the consumer to choose their electricity source. It can also help the providers to estimating the energy consumption and power demand for a short period.
For price forecasting, the same models can be applied, but price forecasting depends on a lot of factors as it mentioned previously in figure 4.1. Such process give a very short term prediction. Also, not all of the conditions are available for the consumer. So the price forecasting will be inefficient for the consumers.

4.2.3.2 Stochastic models data preparations

Unlike time series modules, a stochastic model is a tool for estimating probability distributions of Possible results by allowing random change in one or more inputs over time. This change is usually based on changes in historical data for a specific period. Distributions of possible outcomes are derived from a large number of simulations (stochastic Expectations), which reflect the random change in the inputs. This process may be repeated thousands of times to get the output, which reflects on the time of forecasting. The Mrkov model also has the same issue. The advantage of MDP is that there is no need for history, it depends on the current status of the system ”load consumption”. To achieve the forecasting, the load for each hour need to be categorized into ”groups”, usually performed by the electricity providers. It is classified depending on the consumer load each hour. The price of each category change by the time of the category and reach the max on the peak time.

To start with Markov, we first need to build the stochastic matrix, it’s a square matrix used to describe the transitions of a Markov chain. Each of its entries representing a probability. If the probability of moving from i to j is $P_{i,j}$, the stochastic matrix P is defined as:

TABLE 4.4: April 2018 06:00 AM Load category

Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Load	0.571	0.621	0.531	0.611	0.581	6.611	6.581	0.531	0.781	0.611	0.661	0.661	0.661	0.661	0.611
Category	P1	P1	P1	P1	P1	P3	P3	P1	P2	P1	P2	P2	P2	P2	P1

Day	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Load	6.611	6.611	0.661	6.611	0.611	0.571	0.611	0.611	0.651	0.661	0.661	0.661	0.691	2.191
Category	P3	P3	P2	P3	P1	P1	P1	P1	P1	P2	P2	P2	P2	P3

$$\mathrm{P}= \begin{vmatrix} \mathrm{P}_{1,1} & \mathrm{P}_{1,2} & ... & \mathrm{P}_{1,j} & ... & \mathrm{P}_{1,S} \\ \mathrm{P}_{2,1} & \mathrm{P}_{2,2} & ... & \mathrm{P}_{2,j} & ... & \mathrm{P}_{2,S} \\ : & : & : & : & : & : \\ : & : & : & : & : & : \\ \mathrm{P}_{i,1} & \mathrm{P}_{i,2} & ... & \mathrm{P}_{i,j} & ... & \mathrm{P}_{i,S} \\ : & : & : & : & : & : \\ : & : & : & : & : & : \\ \mathrm{P}_{S,1} & \mathrm{P}_{S,2} & ... & \mathrm{P}_{S,j} & ... & \mathrm{P}_{S,S} \end{vmatrix}$$

To build a stochastic matrix, a classified of the load in certain hours per day to three categories for 29 days was prepared. This categorization was chosen depending on the range of consumption for the consumer. These categories are P_1 [0 - 0.655] KWh, P_2 [0.655 - 1.31] KWh and over than 1.31 KWh P_3. To complete the matrix, we need to calculate the conditional probability functions of transfer from one category to another. Conditional probability functions can be written as follows:

$$P_{i,j} = \frac{Count(j,i)}{Count(j)}, P_{i,i} = \frac{Count(i,i)}{Count(i)} \tag{4.1}$$

In order to explain how the algorithm works,a sample of the data was chosen in April at 06:00 AM, and apply MDP to it. The MDP must be work if the data changed, but the results my be changed according to the input data.
Table 4.4 is a sample of daily load profile at 06:00 AM during April 2018 [1 to 29 April 2018]. To apply Equation 4.1, we need to calculate $Count(i)$, $Count(i,i)$ and $Count(j,i)$. From this sample table 4.4, P_1 count is 13 times, P_2 count is 10 times and P_3 count is 6 times.

To calculate $Count(j,i)$, some assumptions was made according to the sample. $Count(2,1)$ means how many times P_2 comes after P_1, which is 3 times, Count(3,1) means how many times P_3 comes after P_1, which is two times, Count(2,3) means how many times P_3 comes after P_2, which is two times also, Count(1,2) means how many times P_1 comes after P_2, which is two times, Count(1,3) means how many times P_1 comes after P_3, which is also two times, Count(1,1) means how many times P_1 comes twice, which is 8 times, Count(2,2) means how many times P_2 comes twice, which is 6 times, Count(3,3) means how many times P_3 comes twice, which is two times.

Now, we have the following:

$$P_{1,1} = \frac{Count(1,1)}{Count(1)} = \frac{8}{13} = 0.615 \tag{4.2}$$

$$P_{1,2} = \frac{Count(2,1)}{Count(2)} = \frac{2}{10} = 0.200 \tag{4.3}$$

$$P_{1,3} = \frac{Count(3,1)}{Count(3)} = \frac{2}{6} = 0.333 \tag{4.4}$$

$$P_{2,1} = \frac{Count(1,2)}{Count(1)} = \frac{3}{13} = 0.231 \tag{4.5}$$

$$P_{2,2} = \frac{Count(2,2)}{Count(2)} = \frac{6}{10} = 0.600 \tag{4.6}$$

$$P_{2,3} = \frac{Count(3,2)}{Count(3)} = \frac{2}{6} = 0.333 \tag{4.7}$$

$$P_{3,1} = \frac{Count(1,3)}{Count(1)} = \frac{2}{13} = 0.154 \tag{4.8}$$

$$P_{3,2} = \frac{Count(2,3)}{Count(2)} = \frac{2}{10} = 0.200 \tag{4.9}$$

$$P_{3,3} = \frac{Count(3,3)}{Count(3)} = \frac{2}{6} = 0.333 \tag{4.10}$$

After calculate the Conditional probability functions, the transition probability matrix will be:

$$\begin{vmatrix} 0.615 & 0.200 & 0.333 \\ 0.231 & 0.600 & 0.333 \\ 0.154 & 0.200 & 0.333 \end{vmatrix}$$

Note that the sum of probability values from each column is equal to 1, which means that this matrix is stochastic matrix[32]. Figure 4.10 represent the Markov diagram for 06:00 AM during April 2018.

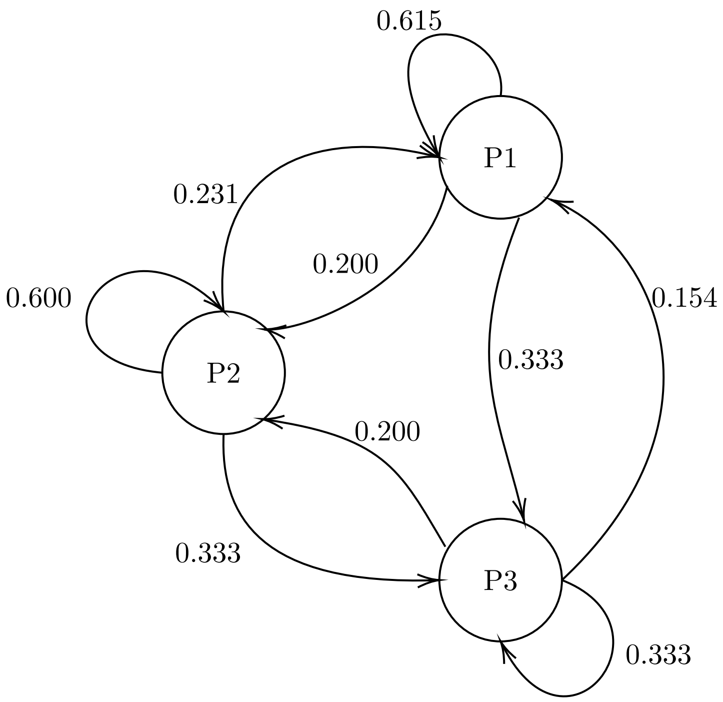

FIGURE 4.10: Markov diagram for 06:00 AM during April 2018

Now, after Markov diagram is done, MDP will be implemented using Matlab. We need to know that the Markov model will forecast a category from the range of data, which means that some data will disappear due to the grouping process. This problem can be solved by decreasing the range of each category, or by using a standard categories provided by the supplier. Usually they give a dynamic price depending on the consumption rate.
Note that using more categories increases the dimensions of the probability matrix, which also causes more complexity with Markov models.

4.3 Summary

In this chapter, The methodologies that were used to forecast the load were decided, even by using Time series models like ARMA model, or using stochastic models. Also, in this chapter, a full description of how the data are collected will be given. Such data will be prepared to be the input of the models.

After getting the results, a comparison will be done to calculate the errors. The comparison will be with the real data from the suppliers. After that, a comparison will be made between the different forecasting models to see which one gives the beast forecasting results.

Chapter 5

Experiments and results

5.1 Experimental environment settings

In this chapter, the models that were described in Chapter 2 were evaluated by writing codes using Matlab simulator. As discussed in the previous chapters, load forecasting is a process that depends on the behaviour of the consumer. However, to complete such forecasting, we need to collect some information about the history of the consumer load profile. In this chapter, It has been used the forecasting for load consumption hour by hour with previous load profile for one month. The time series forecasting model that was used takes the load profile from the electricity providers, and then derives the load prediction for short to medium time forecasting. For a stochastic model, the Markov model was chosen to generate short term forecasting as discussed in chapter 4.

5.2 Time series model implementation

Tables A.1 and A.2 in Appendix A, show the daily power load consumption hour by hour, with the average temperature, that was discussed in chapter 4, for a city in Norway from April 1st to April 30th, and from June 1st to June 30th. The classical time series model (ARMIA) is applied to forecast load. The prediction results of the model are compared with the results from stochastic model (MDP).

The ARIMA model is able to identify complex patterns in the data set time and therefore, it is widely applied for short-term forecasts. Generally, ARIMA includes an autoregressive process, difference to strip the integration and moving average, where the polynomial p is the order of the AR model, the polynomial q is the order of the MA model and the polynomial d is the order of difference applied to ensure the stationary of the data set.

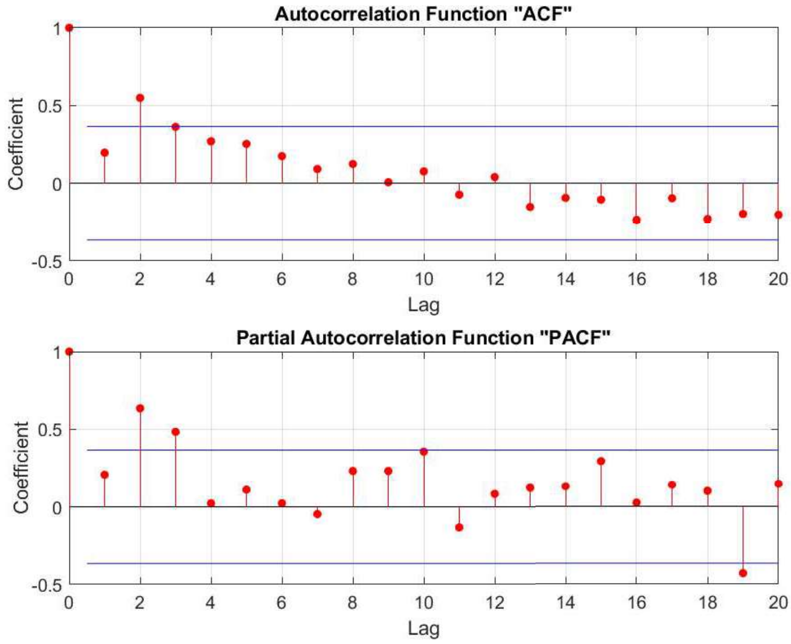

Figure 5.1: Sample ACF and PACF plots for differences time series

To determine the order of (p) and (q) lags, estimated regression models with ARIMA(p, 0 , q) errors by varying (p) value from 0 to 5 and (q) to 2. The best fitting model is this case determined with the lowest Bayesian Information Criterion (BIC) value as shown in figure 5.1, from BIC matrix. The rows represent the AR degree (p) and the columns represent the MA degree (q). The smallest value is best.

Table 5.1: BIC matrix

-48.3522	-66.9589	-71.5825
-61.4723	-65.0703	-70.1814
-65.7203	-69.6967	-68.4821
-65.0468	-77.2367	-66.9326
-76.0552	-77.8930	-76.9364

As seen in table 5.1, the smallest BIC value is -77.8930 in the (5,2) position. This gives us the best p and q for the ARIMA model to an ARIMA(5 , 0 , 2) model. The real data is shown in figure 5.2.

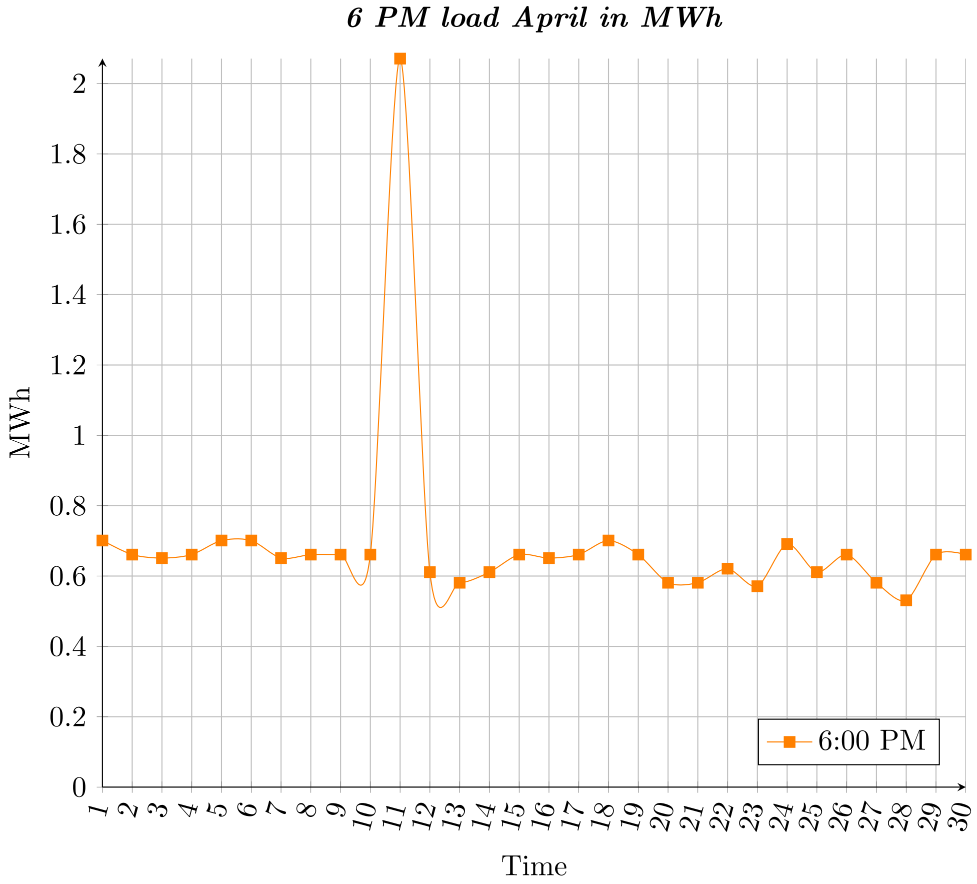

Figure 5.2: 6:00 PM April real load

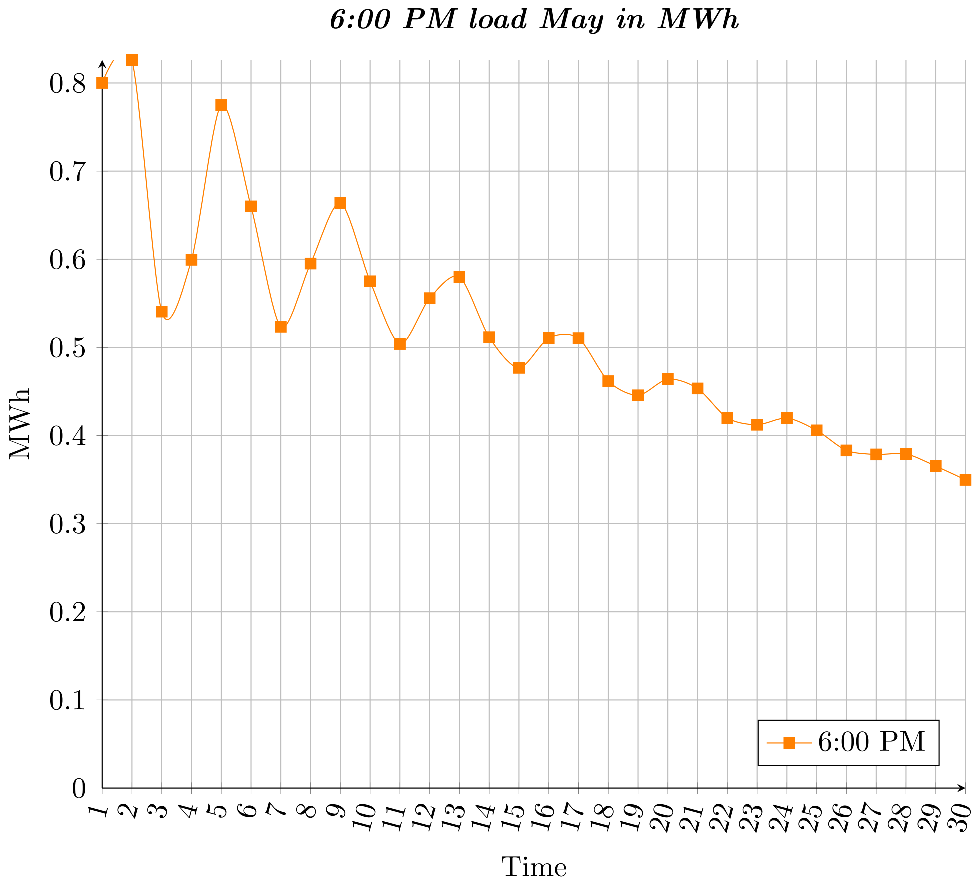

Figure 5.3: May 2018 in Forecasting load

Figure 5.4 shows the expected load for May 2018 after applying the ARIMA model, as it's clear from the figure, the forecasted load for 06:00 PM were driven from the load from April 2018 06:00 PM.

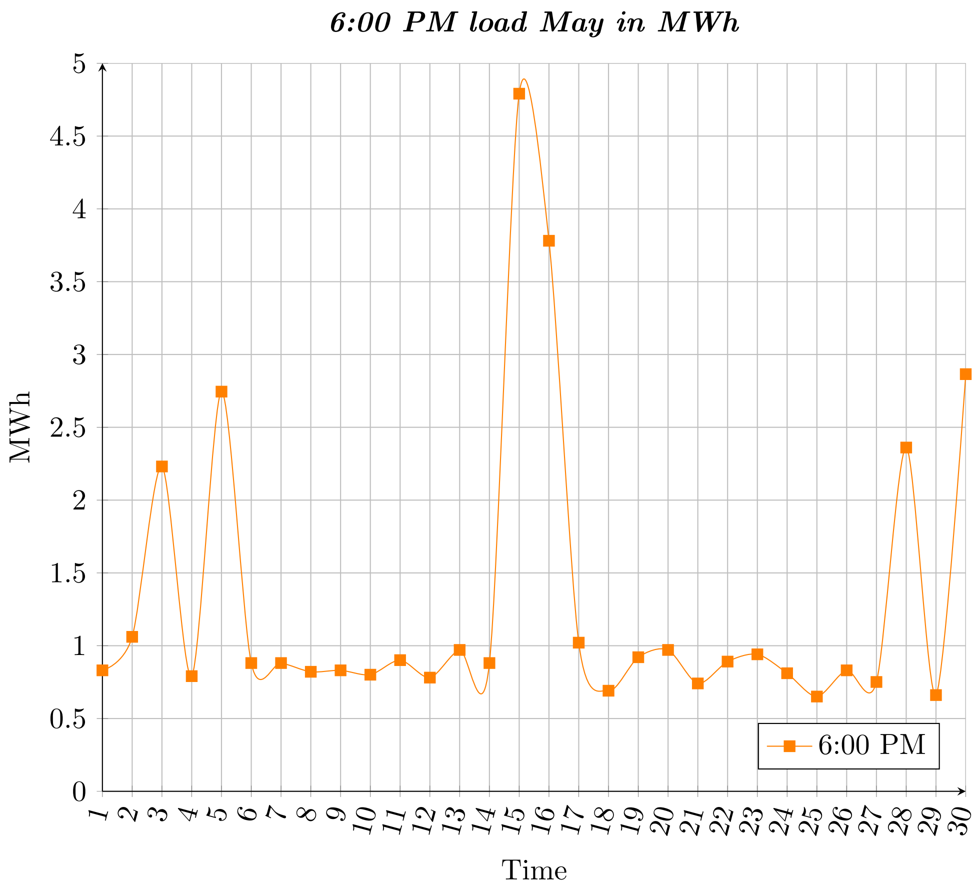

FIGURE 5.4: 06:00 PM May 2018 forecasted load using ARIMA model

From figures 5.3 and 5.4, we can see the load of actual and forecasted load curves. Table 5.2 is a comparison of the first five days in May between the real load data and the forecasted data. We can see that the error percentage increased for the long time forecast that generated by the ARIMA model "more than one day", which is about 3.7% for 1st of May and 24% for 4th of May.

Such range of error will be changed from one month to others, and also from a consumer to another. The other parameters like the temperature and the wind speed will affect the results.

This change on the forecasted load depends on the previous data and the change of the load during the time of the study.

Table 5.2: Error percentage for forecasted data May 2018

Date May	Forecasted MWh	Actual MWh	Error
1	0.800119341	0.831	3.716084116
2	0.826070761	1.061	22.14224684
3	0.540576013	2.231	75.76978875
4	0.599359085	0.791	24.22767573

Table 5.3 is a comparison of 5 days in July between the actual load data and the forecasted data. The error percentage increased for the long time forecast "more than one day", which is about 4.8% for 1 July and 20.1% for 4 July.

Table 5.3: Error percentage for forecasted data July 2018

Date July	Forecasted MWh	Actual MWh	Error
1	0.800119341	0.841	4.860958312
2	0.826070761	2.471	66.56937429
3	0.540576013	0.691	21.76902847
4	0.599359085	0.751	20.19186613
5	0.774889749	0.871	11.03447198

5.2.1 Root Mean Square Error

he Root Mean Square Error (RMSE), or the root mean square deviation (RMSD) is a commonly used measure of the difference between values forecasted by a model with the actual values. The RMSE used to combined them into a single measure of predictive power[39].
The RMSE of a predicted data with respect to the estimated variable $\hat{X}$ is [39]:

$$REMSE = \sqrt{\sum_{t=1}^{n} \left(\frac{[\mathrm{X(t)} - \hat{\mathrm{X}}\mathrm{(t)}]^2}{\mathrm{n}} \right)} \tag{5.1}$$

Where t is current iteration, n is the number of samples, X is actual value and $\hat{X}$ is predicted value.

Figur 5.5 shows plots that depicts predicted points by ARIMA. Regression line among predicted and desired values clearly shows that RMSE is greater so that there is huge

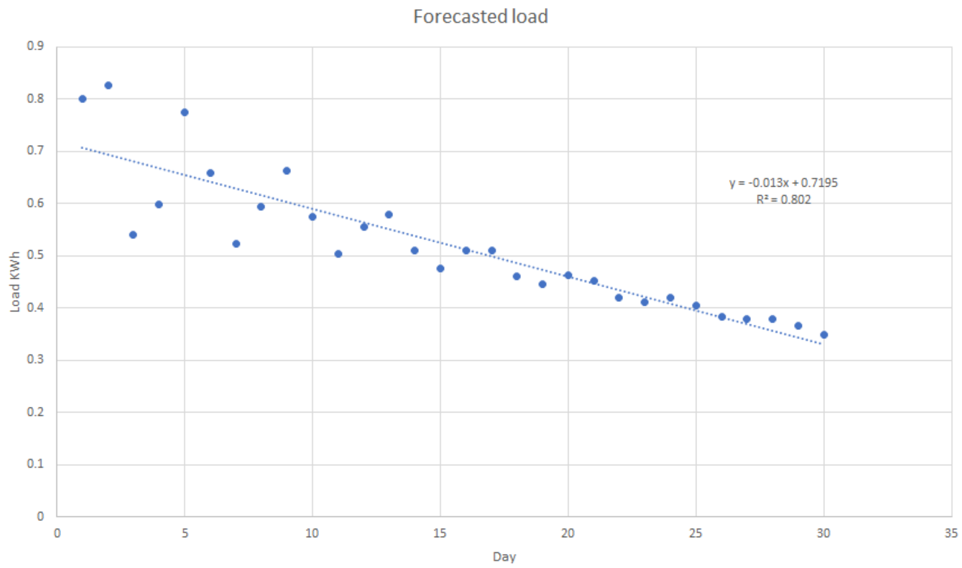

FIGURE 5.5: Forecasted load for May.

difference in desired and predicted values.it shows that the load predicting for May valued RMSE average for the entire year was 0.22. and type 1 input valued RMSE was 0.05165.

5.2.2 Stochastic model implementation

The Markov model deals with discrete time intervals, which means that we need to classify the load into intervals. Those intervals can be created depending on time during the day, load consumption or KWh price. The selected categories was discussed as previews in chapter 4, table 4.4.

April 29th, 2018 6:00 PM, the load was 2.865 KWh, which is in the last category. After applying MDP, the next step is to be in the same category as shown in figure 5.6. NOORD POOL data [6] shows that the load in April 30th 6:00 PM 2018 is 2.431 KWh, which is in the same category of the previous day at the same time.
In this case, MDP will not give us the expected load, it will provide us with range of possible load consumption that is expected to be for the next day. Figure 5.7 shows the evolution of transition probability for each load group using the Markov model.

Error percentage from using MDP for load forecasting will not be efficient. The result of this prediction is used, usually, in the very short term of load consumption. However, the result is not specified by exact load consumption. Such forecasting will be useful for power providers with a huge number of consumers, so that the load consumption for consumers will be in Megawatt/hour or more.

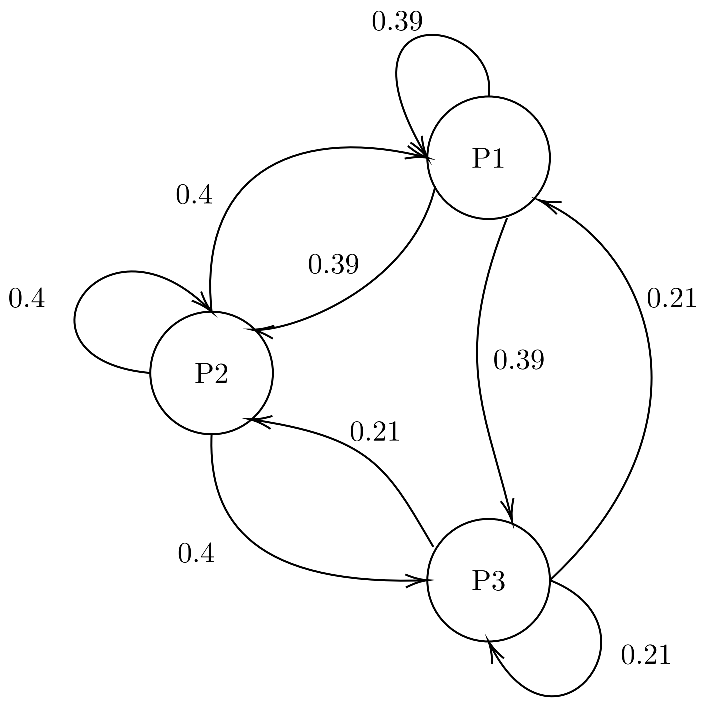

FIGURE 5.6: Markov diagram for 08:00 AM during April 2018

For 8:00 AM, which was the peak time in April 2018, the following is the MDP conditional probability:

$$P_{1,1} = \frac{Count(1,1)}{Count(1)} = 0.25 \tag{5.2}$$

$$P_{1,2} = \frac{Count(2,1)}{Count(2)} = 0.200 \tag{5.3}$$

$$P_{1,3} = \frac{Count(3,1)}{Count(3)} = 0.4545 \tag{5.4}$$

$$P_{2,1} = \frac{Count(1,2)}{Count(1)} = 0.25 \tag{5.5}$$

$$P_{2,2} = \frac{Count(2,2)}{Count(2)} = 0.5 \tag{5.6}$$

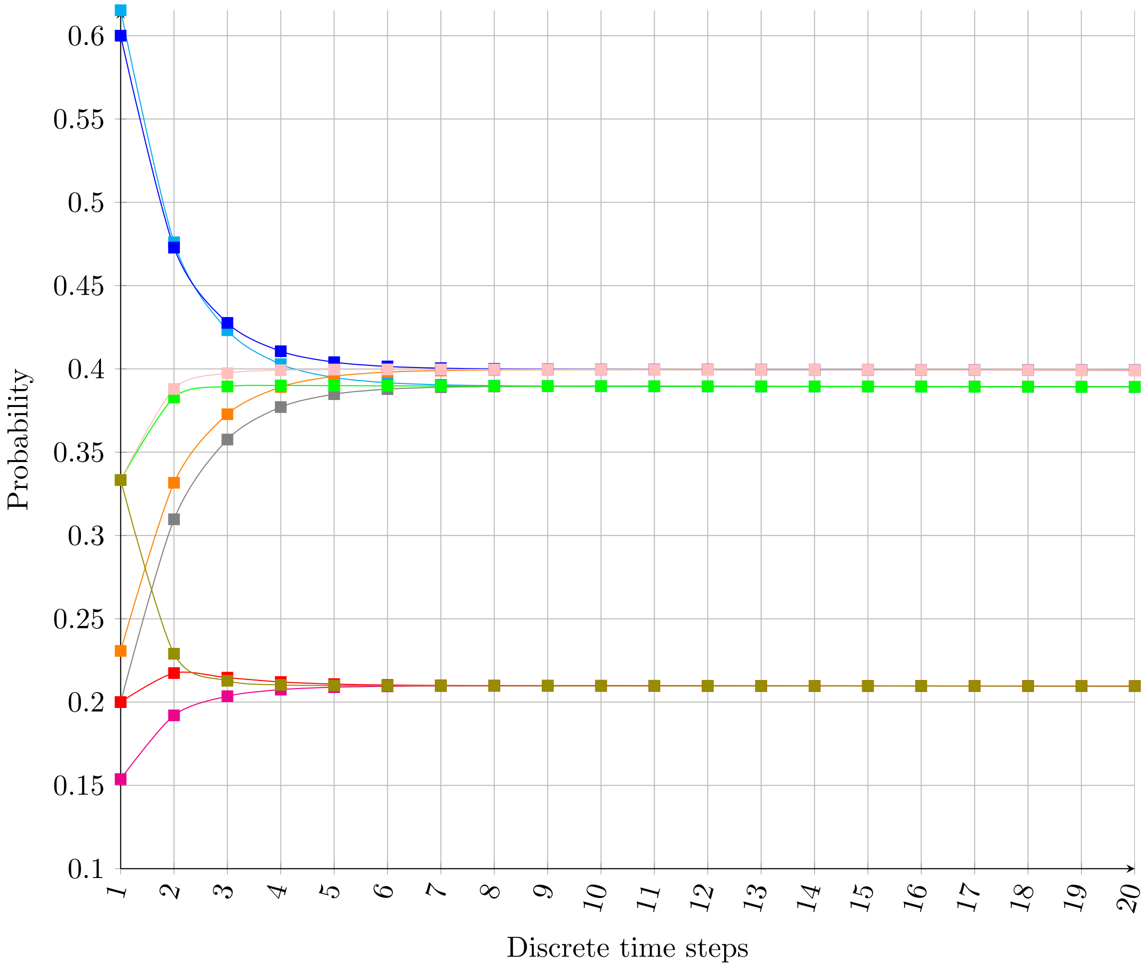

FIGURE 5.7: Evolution of transition probability for each load group

$$P_{2,3} = \frac{Count(3,2)}{Count(3)} = 0.2727 \tag{5.7}$$

$$P_{3,1} = \frac{Count(1,3)}{Count(1)} = 0.5 \tag{5.8}$$

$$P_{3,2} = \frac{Count(2,3)}{Count(2)} = 0.3 \tag{5.9}$$

$$P_{3,3} = \frac{Count(3,3)}{Count(3)} = 0.2727 \tag{5.10}$$

After calculating the Conditional probability functions, the transition probability matrix will be:

$$\begin{vmatrix} 0.25 & 0.20 & 0.4545 \\ 0.25 & 0.50 & 0.2727 \\ 0.50 & 0.30 & 0.2727 \end{vmatrix}$$

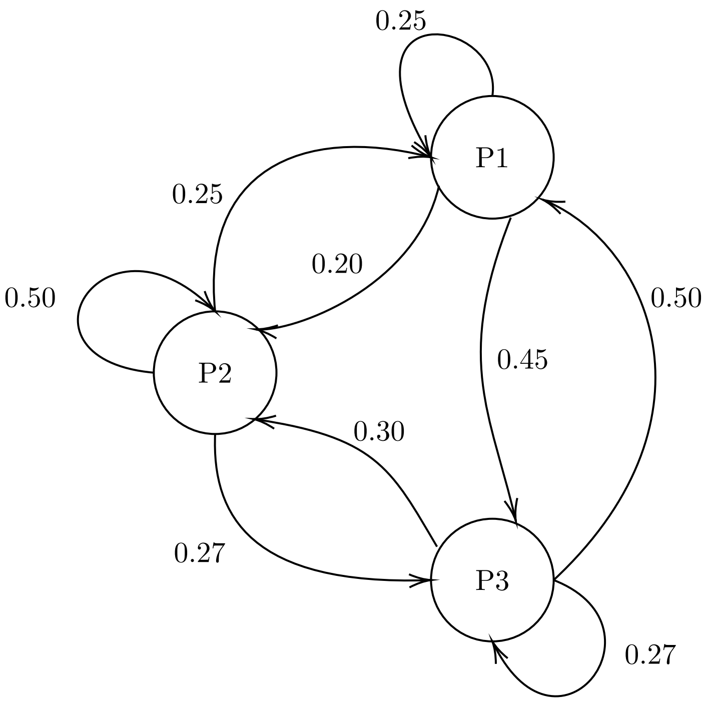

FIGURE 5.8: Markov diagram for April 2018 8:00 AM

April 29th, 2018 8:00 AM, the load was 0.741 KWh, which is in category P2. According to figure 5.8, the next step is to be in the same category. Appendix 1 shows that the load of April 30th, 8:00 PM is also 0.741 KWh. Figure 5.9 shows the evolution of transition probability for each load group using the Markov model.

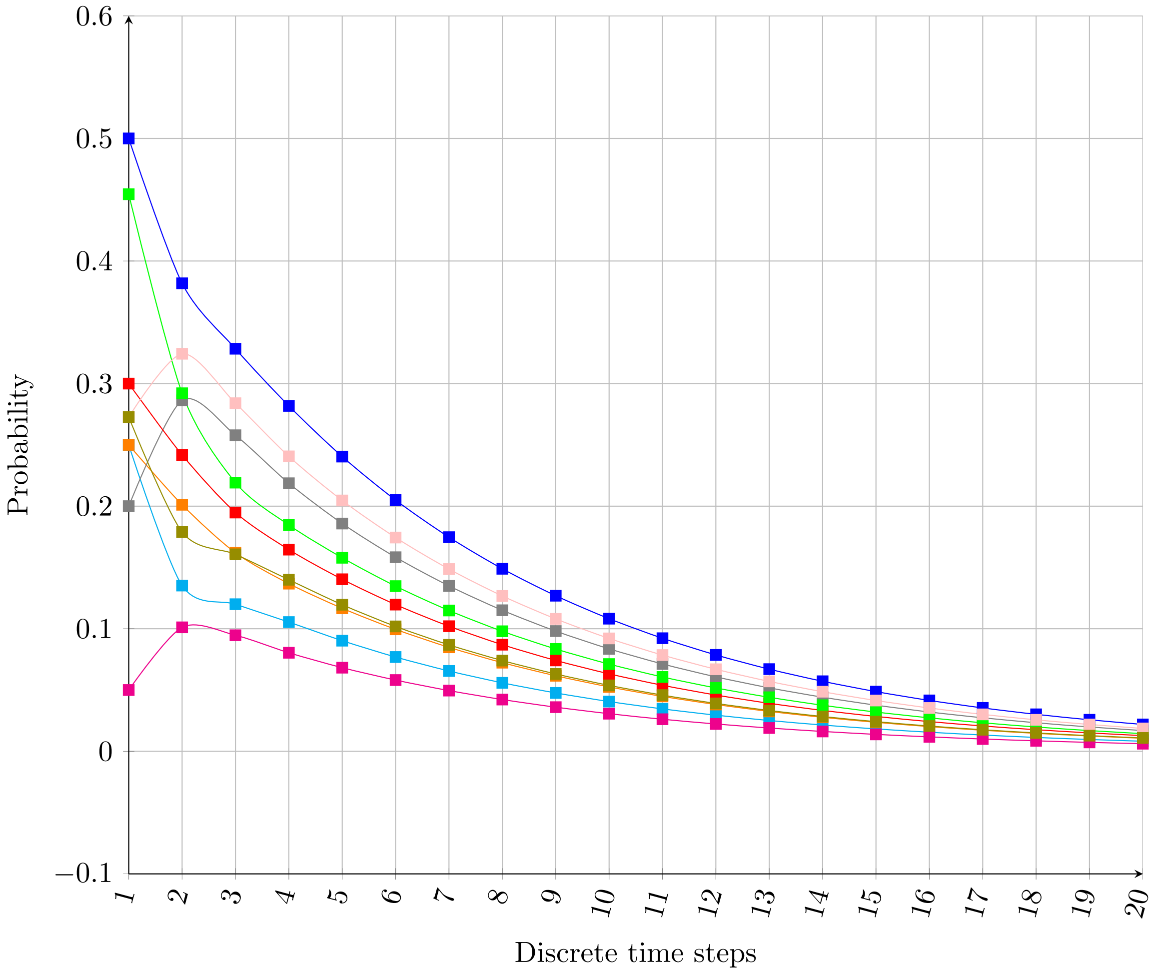

FIGURE 5.9: Evolution of transition probability for each load group in April 2018 8:00 AM

By using the forecasting output of ARIMA model, consumers behaviors will be improved, their purchases from the grid and sales to it. Consumers who generate electricity can sell their excess during the predicted peak times, when they are expected to have an excess at a specific time, based on their predicted future levels of consumption and the expected current storage level if they have. If the storage status is empty, a decision need to be made from the IoT controller. Such as put the generated electricity at that time into the grid. If the storage status is full, the controller then needs to decide whether to consume the sorted electricity or selling it. The controller also will be sure that the minimum amount of electricity will be supplied, even from the grid or from the storage.

An MDP model can be used to improve consumers behaviors for the long-term. As it is shown if figure 5.9 the twill be for rang of load reading, this will be useful to maximize the consumers behaviors for large scale of time. Such as to predict the load in the next weekend. Usually, in weekends the peak-time is not the same as it on the working days.

The controller in such cases can compare between the cast of the electricity on that day and with it on the other days. If its cheaper than the cost on working days, the controller will take a design to sort the generated electricity, and use it on other peak-times where the price could be more expensive.

Chapter 6

Conclusion and future work

This thesis is focused on forecasting a load consumption for consumer in a smart grid system network,where consumers can generate their own electricity. Such consumers can also predict there future levels of electricity consumption with reasonable accuracy. . The proposed method provides us with a real-time forecasting data of electricity load, based on the previous hour by hour load profile. Such systems can help the consumers to decide there next behavior, like sorting energy using local power storage or not. Such forecasting can be achieved by using models like the ARIMA model and the MDP model, which is used to improve consumers behaviours (their purchases from the smart grid and sales to the smart grid) during each specific decision period, in order to maximize their net benefits considering various factors. The proposed schemes(ARIMA and MDP) were compared with the actual load data from the market, the results of extensive studies show that the proposed scheme significantly outperforms the baseline competing scheme.

The ARIMA model provides an Acceptable level of load forecasting for short time forecasting. It can also give a long time load forecasting, but the error percentage in this case will be increased. For one day forecasting, the ARIMA model gives us an error percentage of about 3.7% to 4.8%, which is acceptable for small to medium consumers.

MDP also gives a load forecasting for the same load. It provides us with a forecasting range for the load consumption, but it's short time forecasting. The error rate will be very high because the data will be categorized with limited numbers of groups. This model quickly produces forecasting results, but it does not give an exact load, the result will be included in range of load records.

Load forecasting can improve the way of how the electricity companies in Palestine supply ; such studies give a future look to the future needs of Palestine, which will allow for the Palestinian Energy And Natural Resources Authority (PENRA) to put a future plan in place for renewable resources to cover the future needs of the Palestinian market.

In addition, load forecasting can be used to limit the electricity theft in the national grid by using the data which is used to forecast the loads. Get the expected load and compare it with the real loads and prices, if there is a significant difference between the real and the expected load; there is a high possibility of electricity theft or faults.

For future improvements, adding extra information to the load profile, such as weather forecasting, can improve the data for the forecasting results. The challenge for adding data will be in the complexity of the forecasting algorithm. More complexity needs more hardware resources. IoT devices currently have limited hardware resources. Because of this, we need a technological updates in our hardware to achieve such forecasting with extra information.

Another possible option for the load forecasting is to forecast average day load consumption, using the same algorithms or other forecasting algorithms. We can also predict the future price from the energy distribution companies.

Appendix A

Appendix

TABLE A.1: Load profile for April 2018 MWh

Hour\Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
6	571	621	531	611	581	6611	6581	531	781	611	661	661	661	661	611	6611	6611	661	6611	611	571	611	611	651	661	661	661	691	2191
7	8281	781	6611	581	6611	6611	6651	661	661	6581	621	581	661	621	571	6621	6611	531	6691	841	661	621	531	2261	611	661	701	801	791
8	6661	691	6661	651	6611	6611	6701	611	581	6701	651	761	761	741	701	6691	6701	741	6581	581	2271	811	781	651	2071	571	611	841	741
9	6651	691	6571	2501	6811	581	701	721	611	6661	751	771	611	2825	661	6741	661	691	651	611	761	571	651	691	761	611	611	581	651
10	6701	2581	6611	2951	6761	651	691	801	571	6611	6891	701	2151	961	531	701	611	801	611	701	611	571	531	721	891	801	671	661	8071
11	571	661	661	2711	6991	801	2151	941	611	841	8541	691	661	2531	801	801	611	811	581	701	661	661	611	721	801	531	801	611	6651
12	701	611	581	831	2431	721	771	771	661	621	6931	651	611	741	651	571	661	4351	941	571	531	581	661	661	731	741	701	571	8201
13	651	611	611	621	2231	751	2341	611	581	751	841	661	611	721	571	651	531	2731	801	801	611	611	701	611	651	731	571	611	571
14	531	611	611	611	781	721	2191	661	2501	841	661	701	581	621	741	661	611	2291	661	891	651	661	611	731	791	881	751	661	651
15	661	581	611	611	981	651	811	571	721	581	741	641	611	581	691	2201	621	571	691	731	741	611	691	801	721	701	571	581	791
16	2201	791	661	611	851	651	2611	701	571	791	781	731	611	651	631	851	701	781	1071	731	2071	2241	2211	741	2441	2271	731	651	4425
17	691	2331	781	701	791	2121	2121	841	881	851	841	781	941	791	2421	881	2241	731	831	1011	731	2391	4081	1101	2331	2151	741	801	2801
18	731	881	761	10071	1131	2241	881	841	831	781	2331	841	2521	781	2675	821	831	891	1081	4201	921	2641	2441	2841	751	2421	651	661	2865
19	1011	7401	3031	7341	1731	1091	3101	1151	1201	1201	1271	1161	1441	771	4681	901	2721	1621	3111	1181	981	991	1151	1251	841	881	1091	651	1061
20	1241	7421	1261	7581	1441	1561	3031	1371	1081	1231	1611	2851	1721	1201	3481	1171	3121	1531	4411	1351	1181	1501	1131	1571	771	3121	1561	1071	3191
21	1351	7321	1191	7401	3431	1271	1511	1401	2401	1351	1501	1191	1351	1401	1501	1221	1561	1611	4451	1191	1121	1431	1181	1351	3921	1501	1351	1451	1521
22	1111	10371	1281	1401	1451	1691	1461	1021	871	1521	1451	1111	821	1191	1301	1121	1161	1431	1241	921	1031	1351	871	921	4231	1181	1091	1281	3421
23	661	1031	661	1151	1411	1311	921	691	661	1111	1341	821	871	871	951	661	7081	1081	1001	571	771	1031	611	871	3841	951	921	1191	1321
0	581	6611	581	6661	661	811	811	531	6611	611	611	611	6531	611	6661	661	581	6761	661	661	611	661	611	611	921	3611	611	6661	581
1	611	6661	661	6661	611	661	761	661	6661	531	661	611	6611	6611	6661	611	611	6681	611	611	611	6531	531	531	6791	611	611	6611	611
2	611	6661	611	6531	611	611	611	581	6581	661	531	661	6661	6661	6531	611	661	6661	581	581	581	6611	611	661	6661	611	661	6661	611
3	581	6531	531	6661	531	611	531	611	6611	611	661	661	6531	6661	6611	661	531	6611	661	611	611	6611	661	531	6611	661	611	6661	611
4	661	6531	661	6611	581	6611	6661	581	6611	611	531	611	611	6611	6611	581	6611	581	661	611	611	6581	581	611	6531	611	531	6661	581
5	611	6611	661	661	611	6661	6661	611	571	581	611	661	581	6611	581	611	6581	611	6531	581	701	6661	611	661	6531	611	611	581	661

TABLE A.2: Load profile for June 2018 MWh

Hour\Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
6	701	661	651	661	741	701	701	651	661	661	661	2071	611	581	611	661	651	661	701	661	581	621	571	691	611	661	581	531	661
7	571	661	2201	651	611	581	651	621	771	701	841	2241	611	661	611	621	571	621	661	531	701	781	701	741	2241	651	611	611	571
8	701	3651	2161	581	701	731	791	611	651	691	691	741	701	701	3781	651	791	651	2151	651	701	661	3791	791	611	621	741	2201	611
9	741	771	661	701	701	651	691	801	661	791	781	621	741	611	571	801	741	611	531	841	581	581	791	701	581	751	651	2201	691
10	611	2451	611	651	771	651	781	671	701	581	4161	571	661	791	741	611	2161	581	701	691	841	611	661	651	661	801	741	651	661
11	801	4121	571	621	3961	661	701	691	701	611	701	651	781	831	2491	611	611	661	701	791	2231	611	661	2411	611	671	651	531	721
12	801	771	701	751	801	741	691	691	731	661	751	571	771	701	761	581	691	661	571	2031	881	581	581	731	661	2151	691	651	571
13	2421	2491	611	611	611	2201	661	701	611	611	761	661	811	571	881	611	2471	661	701	2241	991	611	611	761	611	701	741	701	651
14	881	701	611	581	751	791	1031	741	531	611	851	611	831	741	2421	531	771	661	611	691	701	581	711	801	651	651	571	731	3921
15	531	701	661	611	721	791	691	751	801	2151	2151	671	911	651	841	531	651	651	581	871	731	751	701	651	741	651	761	721	891
16	2191	531	661	921	751	2701	2221	571	691	721	751	661	841	861	2351	741	2151	601	2541	881	831	701	2271	741	2621	741	861	871	851
17	731	731	651	971	731	941	691	2521	661	731	831	581	871	841	2371	2231	581	681	2501	691	781	751	1061	671	741	741	2595	781	971
18	741	811	2261	801	841	611	2621	831	2291	791	701	691	751	751	2451	821	931	761	2851	911	2371	731	1191	571	661	771	2775	781	981
19	841	681	1111	771	2421	1071	1061	751	871	981	651	801	791	871	2701	4535	981	881	2841	961	931	1161	981	2231	741	831	961	2641	871
20	791	891	1011	951	911	1261	911	921	831	881	861	761	871	921	2441	1021	981	1081	1201	2461	1021	1131	1401	881	891	801	2841	1131	2551
21	981	1031	1441	1271	1251	1681	1121	1271	1241	1151	1091	1071	1581	1041	1261	3311	1191	921	1221	2821	1171	1451	1361	1281	931	1391	1201	951	1071
22	601	1071	951	851	1321	1351	1191	831	1241	1111	981	951	1081	1111	1371	1561	1401	951	1351	1241	921	1271	1401	1351	1201	951	1161	2741	1231
23	1061	951	861	801	971	1191	1241	871	1031	661	581	821	841	1141	1181	1271	691	821	1241	871	921	1121	1241	1031	1031	1221	821	1261	961
0	581	661	531	531	661	531	661	611	581	531	581	611	611	611	531	581	611	611	661	661	661	611	531	611	531	611	611	611	611
1	531	531	661	661	531	661	531	611	661	661	611	611	581	661	531	531	661	661	581	611	611	531	611	661	661	661	531	611	581
2	611	611	611	581	611	531	611	661	611	611	611	581	611	531	661	611	661	531	661	531	581	611	611	531	611	661	661	611	611
3	661	661	581	661	661	661	611	611	531	611	531	661	611	661	611	611	611	661	661	611	661	581	661	611	581	531	531	581	611
4	531	531	611	661	581	661	661	611	611	531	661	661	661	661	611	581	531	611	531	661	611	611	611	661	611	611	611	661	581
5	661	611	661	611	611	531	581	611	701	661	661	661	581	611	661	611	2161	581	661	581	611	611	661	571	581	661	661	661	661

TABLE A.3: Price profile for April 2018 EUR/MWh

Hour\Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
6	39.51	39.96	41.89	42.54	42.25	42.25	38.38	39.04	42.75	40.77	40.36	40.8	40.63	37.71	39.12	44.93	43.77	42.58	40.96	38.86	33.21	34.85	38.16	36.44	37.93	37.33	38.62	35	34.56
7	39.39	39.62	45.38	48.78	47.03	47.03	38.83	38.92	50.05	43.4	42.8	43.63	42.89	38.84	39.56	55.52	52.99	51.6	49.37	41.44	34.77	35.78	41.65	38.33	40.91	42.05	41.69	36.04	34.88
8	39.62	40.33	49.91	58.02	50.21	50.21	39.9	39.42	61	44.86	44.69	44.38	42.93	39.72	39.85	64.26	52.59	56.95	49.96	43.1	35.26	36.42	44.33	38.56	42.13	45.11	45.02	36.85	35.61
9	39.61	40.56	47.82	51.98	48.78	48.78	40.48	39.82	51.27	43.41	42.39	41.82	42.35	39.92	40.13	57.6	50.08	48.99	46.2	41.89	34.47	36.9	41.86	37.85	41.5	40.67	44.37	37.63	35.97
10	39.52	40.63	44.61	46.66	46.4	46.4	40.52	40.05	47.71	41.85	41.58	40.91	41.3	39.87	40.57	53.48	46.72	44.88	43	41.27	34.5	37	40.15	37.12	40.56	38.91	42.14	37.37	36.03
11	39.17	40.32	43.93	44.48	44.26	44.26	39.72	39.84	44.73	41.04	40.66	40.32	40.47	39.77	40.33	50.1	43.65	42.71	41.73	39.35	33.95	36.97	38.63	36.89	39.64	37.96	40.17	36.98	35.97
12	38.86	39.91	43.22	42.4	42.76	42.76	39.12	39.49	42.94	41.85	40.33	40.01	39.67	39.47	39.89	50.07	42.43	41.82	39.92	37.86	31.47	36.49	37.56	36.61	38.9	37.61	38.31	36.21	35.64
13	38.48	39.52	43.16	41.95	42.2	42.2	38.68	39.12	42.49	41.2	40.18	39.87	39.03	39.14	39.5	48.08	41.97	40.9	39.66	36.79	30.04	36	37.27	36.27	38.1	37.48	37.07	35.81	35.32
14	38.15	38.97	42.66	41.31	41.2	41.2	38.19	38.88	41.5	39.83	39.9	39.44	38.95	38.96	39.38	45.77	40.48	39.73	38.73	35.87	27.11	35.67	36.65	35.43	37.4	37.05	36.63	34.99	35.04
15	38.03	38.81	42.3	41.07	40.96	40.96	38.06	38.8	41.32	39.82	39.81	39.32	38.47	38.87	39.33	44.94	40	39.54	38.49	35.33	27.08	35.83	36.63	35.45	36.96	36.68	36.66	34.81	34.57
16	38.13	39.08	42.94	41.03	40.98	40.98	38.17	38.85	41.76	39.76	39.87	39.37	38.96	39.06	39.39	44.33	40.96	39.89	39.4	35.76	29.55	36.09	36.65	35.8	37.03	36.73	37.32	35.14	34.8
17	38.59	39.53	44.52	41.48	41.03	41.03	38.95	39.07	43.69	40.03	40.16	39.47	39.47	39.2	39.64	44.94	42.96	40.99	42.16	37.14	31.39	36.62	36.89	36.38	37.2	36.48	38.09	36.29	35.23
18	39.22	40.11	47.51	42.49	41.39	41.39	39.53	39.46	45.01	40.73	40.4	39.65	39.6	40.23	39.75	47.54	45.73	43.68	42.56	38.38	35.13	36.82	38.02	36.95	37.33	37.18	38.71	37.05	35.6
19	39.64	40.88	49.74	42.77	41.95	41.95	40.49	40.61	45.55	40.91	40.98	40.11	39.66	41.37	41.48	49.65	45.88	44.9	42.41	38.2	36.3	36.91	38.24	37.15	38.65	38.01	38.99	38.25	35.33
20	40	41.09	46.92	44	41.92	41.92	40.52	42.51	43.76	40.31	41.28	39.83	39.48	41.42	42.5	50.35	43.97	43.41	40.74	37.86	36.47	36.96	37.68	37.01	38.83	38.38	38.58	38.52	35.31
21	39.89	40.92	42.88	42.37	40.95	40.95	39.09	41.68	41.01	39.51	40.54	39.46	39.41	41.36	41.73	47.63	42.68	42.69	39.56	37.2	36.34	36.14	37.29	36.77	37.94	38.52	38.49	38.1	35.74
22	39.81	39.96	40.47	40.17	39.93	39.93	38.37	39.91	39.63	39.04	39.73	39.12	39.01	40.95	40.34	43.98	41.59	40.99	38.03	36.16	36.07	35	36.28	36.35	36.48	37.62	37.83	37.01	35.3
23	39.22	39.22	39.13	38.39	38.09	38.09	38.62	38.68	38.01	37.64	38.96	38.5	37.96	40.01	39.18	41.55	39.83	38.04	34.93	32.64	35.34	33.97	34.21	34.77	34.35	35.93	36.02	35.91	33.77
0	39.8	39.38	40.08	39.01	39.13	39.13	38.43	39.03	38.57	38.24	38.15	39.39	38.32	36.58	39.44	38.73	39.99	38.44	35.8	35.01	33	34.78	30.99	32.77	35.73	34.59	35.2	35.91	35.97
1	39.57	38.67	39.36	38.37	38.5	38.5	37.71	38.67	38.02	37.06	37.56	39.15	38.04	36.04	39.17	38.28	39.57	37.63	34.15	32.94	30.42	32.73	27.6	30.17	34.3	31.27	33.39	34.09	34.85
2	39.43	38.43	39.05	38.42	38.49	38.49	37.37	38.54	37.94	37	37.28	39.08	38.01	35.9	38.65	38.16	39.27	36.85	33.89	31.8	29.37	30.96	27.57	29.18	32.63	31.21	32.23	33.32	34.59
3	39.39	38.33	39	38.33	38.95	38.95	37.31	38.75	38.02	37.08	37.73	39.15	38.12	36	38.6	38.36	39	36.42	34.02	32.03	29.04	31.96	27.53	27.08	32.62	31.68	33.12	33.31	34.03
4	39.5	38.61	38.93	38.63	38.9	38.9	37.82	39.03	38.84	37.39	37.94	39.25	38.16	36.3	38.7	38.73	39.04	36.4	34.05	33.3	29.3	33.1	27.65	27.04	33.08	32.64	33.92	32.96	34
5	39.33	39.27	40.41	39.93	40.25	40.25	38.17	39.26	39.81	38.91	39.39	39.57	39.01	36.94	38.77	40.54	39.58	38.05	36.4	35.51	30.24	33.92	35.19	31.7	35.24	35.08	35.77	32.91	33.65

TABLE A.4: Price profile for June 2018 EUR/MWh

Hour\Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
6	45.18	40.47	40.18	44.9	45.9	47.39	47.91	49.33	45.24	44.2	47.62	46.65	47.57	46.69	46.52	42.49	40.55	44.92	42.35	44.49	43.75	39.22	33.9	39.42	46.21	47.1	47.37	47.13	45.21
7	46.22	42.24	41.39	45.62	46.84	48.42	50.91	52.04	46.93	45.52	48.59	47.79	50.51	49.41	46.96	43.91	41.48	47.11	45.07	45.33	46.92	42.41	37.1	40.87	46.52	48.47	47.91	49.13	47.69
8	46.96	43.45	43.08	45.74	46.92	49.02	52.23	54.52	47.43	46.42	49.32	49.5	51	51.63	47.6	44.99	42.96	47.89	45.14	45.55	48.21	43.38	40.15	43.08	47.73	49.09	48.79	50.47	48.97
9	47.29	44.32	43.57	45.81	47.07	49.42	51.1	53.9	48.17	46.46	49.44	49.83	51.92	49.8	47.74	45.44	44.05	47.51	44.85	45.59	46.23	43.47	41.86	43.33	47.93	48.98	48.93	50.29	49.41
10	47.53	43.92	44.03	45.81	47.24	49.93	50.33	53.64	48.21	47.21	49.1	49.88	52.04	48.9	47.9	45.67	44.4	46.69	44.61	45.44	45.2	43.35	42.69	43.96	47.99	49.19	49.02	49.86	49.27
11	47.4	43.6	43.89	45.66	47.52	49.92	49.77	52.87	48.06	47.33	49.2	49.9	52.02	47.97	47.73	45.5	44.43	45.92	44.23	44.81	45.11	42.94	42.51	44.35	48.15	48.96	48.97	49.7	48.94
12	46.81	43.02	43.89	45.64	47.5	48.57	48.91	49.95	47.73	47.21	48.61	50.09	51.22	47.85	47.21	45.06	44.22	45.33	44.08	44.2	44.5	42.03	42.23	44.28	47.87	48.91	49.09	49.32	48.04
13	46.31	42.57	43.46	45.44	47.08	47.86	48.64	49.85	47.38	46.76	48	50	50.86	47.65	46.95	44.54	43.89	45.32	43.97	43.63	43.88	41.89	42.02	44.14	47.9	48.9	49.17	49.15	47.59
14	45.56	42.32	41.62	45.28	46.88	47.87	48.65	49.62	46.87	45.81	47.68	49.93	50.29	47.22	46.66	44.51	43.21	45.07	43.8	43.28	43.57	41.31	41.66	44.24	47.42	48.43	49.04	48.55	46.91
15	44.79	42.22	40.97	45	46.61	47.82	49.11	48.77	46.47	45.21	47.67	49.79	48.12	46.29	46.08	44.4	43.17	44.92	43.4	42.22	42.94	40.39	41.06	43.9	46.35	47.77	48.47	47.59	46.27
16	44.41	42.25	41.32	44.67	46.45	48.32	49.13	48.68	46.65	45.68	47.51	49.01	47.49	45.91	45.88	44.53	43.25	44.52	43.02	41.99	42.04	40.19	40.88	43.91	45.5	46.95	47.88	46.68	46
17	44.63	43.02	42.58	45.44	46.97	48.43	49.31	49.45	47.25	46.67	47.94	49.42	47.93	46.87	46.12	44.87	44.01	45.45	43.53	43.03	42.46	40.97	41.92	44.06	46.44	47.75	48.42	47.38	46.24
18	45.93	43.92	43.57	45.98	47.82	49.08	49.74	49.75	48.41	47.55	48.4	49.33	49.5	47.51	46.49	45.42	44.12	46.41	44.44	43.64	42.81	41.81	42.04	44.32	46.91	48.05	49.18	47.97	47.41
19	46	44.46	44.5	45.98	48.2	49.36	49.85	49.41	48.46	48.46	48.21	49.26	50.37	47.63	46.44	46.14	45.12	46.1	44.77	43.6	43.05	41.07	42.56	44.95	46.79	47.64	49.12	47.78	48.38
20	45.35	43.96	45.11	45.62	47.54	48.33	49.53	48.88	47.96	48.55	47.73	48.7	49.8	47.19	46.21	45.44	45.7	45.25	43.99	43.21	42.51	39.89	42.69	44.9	46.08	47.08	48.19	46.74	48.25
21	45.05	43.96	45.29	45.37	47.16	48.26	49.44	48.84	47.83	48.48	47.58	47.96	49.42	46.86	46.2	45.22	45.92	44.85	43.64	42.97	40.98	37.39	42.63	45.58	45.74	46.79	48.38	45.76	47.91
22	44.95	43.68	44.94	45.27	47.32	47.47	49.21	49.24	47.51	48.49	47.52	48.4	49.54	46.2	46.19	45.62	45.9	44.14	43.63	42.7	39.9	39.16	42.3	45.53	45.65	46.54	47.68	45.68	47.13
23	44.16	42.2	40.66	43.07	44.91	45.17	46.5	47.28	45.29	46.73	45.1	46.11	46.91	41.1	45.56	44.46	44.48	41.49	42.22	41.97	38.05	37.47	41.01	43.27	43.92	44.45	45.29	42.82	44.73
0	41.32	42.15	43.39	38.86	42.66	44.99	44.39	46.01	46.26	45.46	45.35	42.02	46.04	47.3	40.32	43.91	43.84	43.46	40.78	42.06	42.02	42.03	40.64	41.04	42.39	44.09	43.96	44.68	43.03
1	38.54	40.41	41.59	36.21	41.01	42.28	42.53	42.71	43.7	43.95	42.3	40.49	44.01	44.99	38.84	41.61	42.09	40.5	39.11	40.89	40.81	40.23	39.64	39.68	41.37	42.25	42.88	42.55	41.11
2	38.49	39.13	40.04	32.81	39.44	41.24	41.72	42.28	42.07	43.31	41.28	38.9	41.62	42.13	37.95	41.01	40.42	38.94	37.34	39.77	39.84	38.1	39.16	38.59	40.03	41.28	41.91	41.63	38.69
3	38	38.49	39.33	31.92	39.35	41.68	41.48	43.09	41.32	42.19	40.04	39.58	41.16	41.97	36.79	40.67	40.02	37.69	36.86	39.27	39.36	38.13	37	37.54	40.03	41.56	41.48	41.03	38
4	37.99	38.5	38.43	31.45	39.05	41.75	40.81	43.35	40.25	42.08	40.06	39.02	41.18	42.03	37.74	40.25	39.6	36.82	34.42	39.67	38.02	37.91	30.08	36.46	40.61	41.72	41.22	40.03	37.83
5	41.08	38.77	39.25	37.48	41.63	44.64	43.97	46.3	41.92	42.92	43.63	41.73	44.97	44.97	41.93	41.25	39.64	40.85	38.04	41.22	40.14	35.19	35.04	36.38	42.96	43.33	43.82	44.01	42.33

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