Lappeenranta University of Technology
School of Engineering Science
Computational Engineering and Technical Physics
Technomathematics

Kettie Susan Nthakomwa

FORECASTING ELECTRICITY PRICES IN FINLAND'S REGULATING MARKET USING NEURAL NETWORKS

Master's Thesis

Examiners:	Professor Tuomo Kauranne
	Dr. Matylda Jablonska-Sabuka
Supervisor:	Professor Tuomo Kauranne
	Dr. Matylda Jablonska-Sabuka

ABSTRACT

Lappeenranta University of Technology
School of Engineering Science
Computational Engineering and Technical Physics
Technomathematics

Kettie Susan Nthakomwa

FORECASTING ELECTRICITY PRICES IN FINLAND'S REGULATING MARKET USING NEURAL NETWORKS

Master's Thesis

2018

45 pages, 26 figures.

Examiners: Professor Tuomo Kauranne
Dr. Matylda Jablonska-Sabuka

Keywords: Price difference, price direction, regulation/balancing price, neural network, forecast.

Electricity price forecast is vital to market bidders for strategic bidding and to grid operators so as to keep power balanced in the grid. However, studies have shown that electricity spot prices are not that easy to forecast since they are highly volatile. Due to deregulation of electricity markets, markets became more efficient and prices more competitive but this has resulted into regulation markets to be more volatile. This study focuses on forecasting balancing electricity prices which is the difference between regulation and spot prices, and also predicting regulation direction in the Finnish regulation market. Neural networks, which have the ability to handle complex relations in the data are used. A feedforward neural network is implemented in Matlab, where Levenberg-Marquardt Backpropagation algorithm, which works at minimizing the error, is employed in training the network model. The networks are trained, validated and tested for high accuracy and then used to make predictions for balancing price and balancing direction. The results

obtained show that the fitted model for balancing price has a fit performance of 44.01% and the balancing direction fitted model has 45.9% performance.

PREFACE

It is of great joy that I express my wholehearted gratitude to the Almighty God for giving me the grace that has enabled me complete my study to His glory.

My sincere appreciation to Professor Tuomo Kauranne for his ideas, encouragement and constant support that made this study a success. I would like to express my deepest gratitude to Dr. Matylda Jablonska-Sabuka for her guidance and support throughout this learning process despite her busy schedules. I must say I was highly favoured to work under her supervision as she offered a platform for me to learn new ideas and guiding me when loosing track. I also salute all my lectures at Lappeenranta University of Technology for the knowledge and computing skills I have acquired through them. To the Lappeenranta University of Technology administration and staff, am so grateful for the opportunity offered to me so as to pursue my studies at Lappeenranta University of Technology, Finland. I shall forever be grateful.

Finally, my warmest appreciation goes to my parents Mr and Mrs A.D. Nthakomwa, my sister Fatsani, my brothers Emmanuel, Fryson with his family and Gerald with his family, for being there for me. Even though they were at distant, their love and encouraging words were of comfort and a shoulder to lean on. All my classmates and friends that showed love and attention, I salute you all.

Lappeenranta, May 25, 2018

Kettie Susan Nthakomwa

CONTENTS

List of Figures

ABBREVIATIONS AND SYMBOLS

ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
CET	Central European Time
FI	Finland
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
LMB	Levenberg-Marquardt Backpropagation
MSE	Mean Square Error
MWh	Megawatt-hours
NN	Neural Networks
SE1	Sweden bidding area 1
SE3	Sweden bidding area 3
TSO	Transmission System Operator

1 INTRODUCTION

This section gives a general introduction on electricity markets at large. The research background and the objectives of this study are also discussed. Finally, the structure of this thesis is given.

1.1 General introduction

Almost in all developing and developed countries worldwide, financial markets have become a subject that has captivated the interest of researchers. Since their emergence, there has been a drastic change which has led to the introduction of new derivatives both in stock and commodity exchange markets [1]. Recently, commodity markets have experienced such tremendous changes which have resulted in these markets becoming an essential type of financial asset traded all over the world. Trading in commodity markets can be categorized into two: spot and futures markets. In the spot market, commodities are traded for immediate delivery or in the very near future. In the futures market delivery and payments are exercised at some agreed later date. One enters into an agreement to buy a particular commodity at a specified maturity date.

Among all commodities, electricity is characterised with higher levels of demand in specific seasons. Since it cannot be stored, power balance is required in the system to increase or reduce production as well as making it readily available to consumers at all times [2], [3]. Studies have shown that electricity prices are challenging to predict since they are highly volatile. Some factors that contribute to these fluctuations in electricity prices include demand and supply, extreme events in the stock exchange markets or economic crisis and even advancement in technological activities. Therefore, investors who are profit-oriented seek to vindicate themselves from these uncontrollable movement in electricity markets. Having prior knowledge of how the market will behave is vital towards achieving their targets. Different research types have been conducted in trying to provide this information through forecasting electricity prices. However, electricity price forecast still remains a wide field for ongoing research.

Provision of electricity in countries where the state is not in charge of running the power markets seems to be more effective than those that are under government ownership. Theory has it that deregulation of electricity markets made the markets more efficient and the prices more competitive [2] since some of the factors that contribute to high volatility of electricity are monitored. Due to competitive electricity markets, traders need to have accurate instruments for forecasting electricity prices. This is because accurate price prediction helps in providing important information that can be of significance in planning for bidding strategies to both producers and consumers so as to maximize their profits [4]. Additionally, it is vital to grid operators whose main focus is to keep production and consumption balanced. The electricity market considered in this study allows trading in the spot market and in the regulation market. Therefore, traders need to have prior knowledge of both the spot and regulation price forecasts.

1.2 Background of the study

Even though electricity price prediction is a challenge, several studies with different approaches have been carried out to forecast electricity spot prices. These studies have been able to yield some results, however, there are still emerging studies that seek to improve the performance of these models. Different methods have been studied in line with regression techniques, which basically model the relation between response and explanatory variables using the method of least squares. Some of the classical approaches in modelling electricity prices using this regression approach have been reviewed in [2]. The authors present a family of models building up the dynamics of electricity spot market behaviour and some regulation principles in the regulation market. Some of the methods discussed include multiple linear regression models and classical time series models such as ARMA and GARCH. However, the classical time series have a shortfall that they can only be applied to price returns since they require stationary data. Similarly, ARMA and GARCH have a predictive distribution that fails to capture the behaviour of real data [2],[5]. Theory has it that neural networks (NN) have the ability to capture and represent complex dependent and independent variable relations that cannot be captured by linear regression models. For instance, NN networks were applied in predicting hourly electricity spot prices in the Mainland Spain electricity market [6]. In their study, the authors made a comparison of the ARIMA method to that of the NN approach. It was discovered that NN approach outperformed the ARIMA technique in all seasons. Additionally, NN appeared to have a higher execution speed than ARIMA techniques, making NN advantageous over regression techniques [6]. Similarly, the same was observed in a another study where a hybrid electricity forecasting model for Finland electricity market was proposed [7]. An artificial neural network model was one of the models that showed an improvement in the performance of predicted results out of eight techniques that were analysed. However, it has been discovered that there is little research work that has been published so far in forecasting Finland's regulating prices in the Nordic electricity market.

Some research work has been done in regards to the overall regulation power market. Analysis has been made on how the regulation power market is affected if bidders fail to meet up their original commitments on the market [8]. Some preliminary analysis on the difference between the spot and regulation price instead of the actual regression price in forecasting for wind power prices were considered [9]. The author discovered that modelling their difference might yield positive results. Even though different aspects of the regulating electricity market have been studied, to our knowledge, there is no literature that has analysed the balancing market in Finland. Therefore, the main contribution of this study to literature is that we are forecasting electricity prices in the balancing/regulating market, whereas most other research in literature focuses on forecasting electricity spot prices. With the discovery made about NN, this study proposes such an approach.

1.3 Objective of the study

The main objective of this study is to forecast electricity prices of Finnish regulation market using neural networks. Specifically, we aim at predicting the regulation price difference, which is basically the difference between regulation price and spot price. It is of interest to know that traders are not necessarily interested in the price of electricity at specific trading hours, but rather in the direction of prices. Therefore, this study also makes predictions on direction of the regulation price difference in each trading hour.

1.4 Structure of the thesis

This study is structured as follows. Section 2 discusses the deregulation electricity market. A brief discussion on the history of Nord Pool power market in Finland is presented with its structure and performance presented in section 2.1. The regulation power market which is the balancing market in our case is also described in section 2.1. Preliminary data description of the factors that are suggested to have an effect on the balancing electricity price is done in section 2.2. Section 3 gives a brief discussion of the NN approach, specifically the NN architecture in section 3.1 and the type of network built for this study is in section 3.2. The algorithm employed is also briefly discussed in section 3.3. Section 4 constructs the network and implements the model. Construction of the model is presented in section 4.1. The results from training, validation and testing the network for regulation price difference are discussed is section 4.2 while that for regulation price direction are presented in section 4.3. Finally, a general discussion on the study is given in section 5.1

together with the some conclusions reached in section 5.2 . Finally, some possible area for further study are also provided in section 5.3.

2 DEREGULATED ELECTRICITY MARKETS

In the 1990's, there was a massive change in the electricity power sector as many developed and developing nations started to restructure their sectors so as to improve their operations. One program that was developed was privatization of state-owned enterprises [10]. The first country to deregulate its electricity sector was Norway [11]. After deregulation of the power market in Norway, an independent power exchange company was introduced in 1993. Nevertheless, Norway had challenges in operating the market since their electric power was hydroelectric and this led to electricity spot prices being highly volatile. On the other hand, Sweden had problems in establishing such a market. This was mainly because Vattenfall and Sydkraft owned a large percentage of the market share that contributed almost 75 percent of the generating capacity in Sweden. In order to handle such challenges in both Norwegian and Swedish markets, a joint market between Norway and Sweden was established. In 1995, the Norwegian-Swedish joint exchange market started operating basing on the Norwegian experiences and this was termed Nord Pool. Later in 1998, Finland power exchange joined the Nord Pool with an agreement to represent Nord Pool in Finland [9].

2.1 Structure of Nordic electricity market

Currently, Nord Pool electricity market is the largest electricity market in Europe. In terms of its market members, Nord Pool has 380 customers from 20 countries with 9 active countries in participation. Total number of companies responsible for production of power in Nordic countries is 380 and there are about 500 distribution companies that are responsible for delivering electricity to end users. Figure 1 is the geographical view of the current Nord Pool structure showing 9 current countries that actively participate in the Nord Pool power market. It also provides services to other countries that are represented by the serviced market in Figure 1. Also, Nord Pool has been appointed as Nominated Electricity Market Operator (NEMO) in the countries represented by expansion market key.

Nord pool operates both in physical and financial markets. In financial markets, derivatives that are traded include forward and futures contracts. The main aim of these financial markets is to provide opportunities that will manage or reduce risks and financial losses for traders throughout the contract period [3], [2]. The Nord Pool physical market is categorized into two: day-ahead which is known as Elspot market and intraday market which

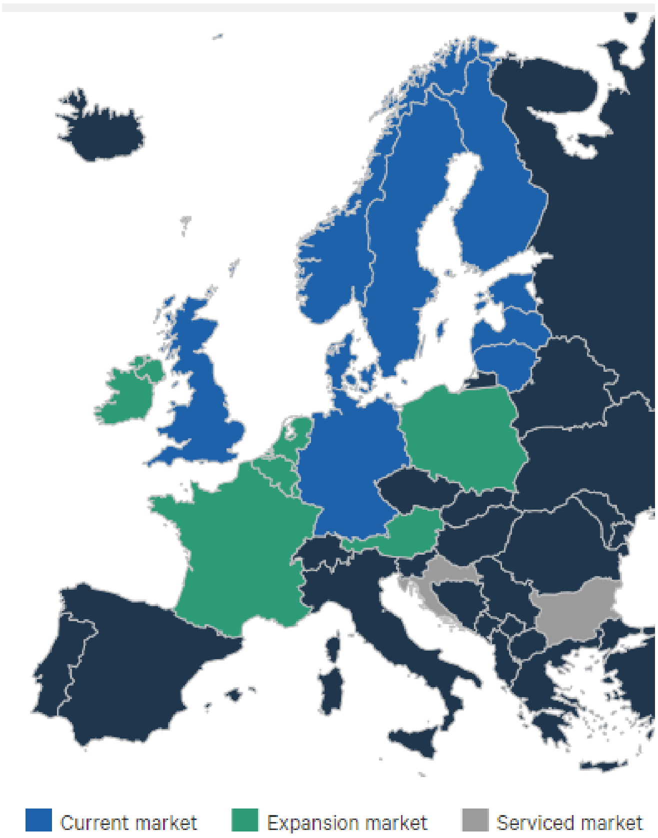

Figure 1. Nord Pool geographical structure (Source: www.nordpoolgroup.com)

is also called as Elbas market.

2.1.1 Day-ahead market

In the day-ahead market, trading is done on the spot market and these are opened every day of the year with public holidays inclusive. Participants are expected to submit hourly buying and selling bids for each specific hour of the following trading day and deadline for submitting the bids is 12:00 CET. Each bid is specified with both the price and volume. At 12:42 CET or later, hourly prices are presented to the market. The buyer and seller enter into a contract for the following day's power delivery, prices are set and a trading agreement is settled. Physical delivery starts from 00:00 the next trading day (hourly) in accordance with the agreement [12].

System price

The market prices are calculated at each trading hour. When the bids are obtained, the information is fed into the system that calculates the prices. Demand and supply curves are built from these bids, and the intersection point between these two curves is what provides the price in that hour as shown in Figure 2.

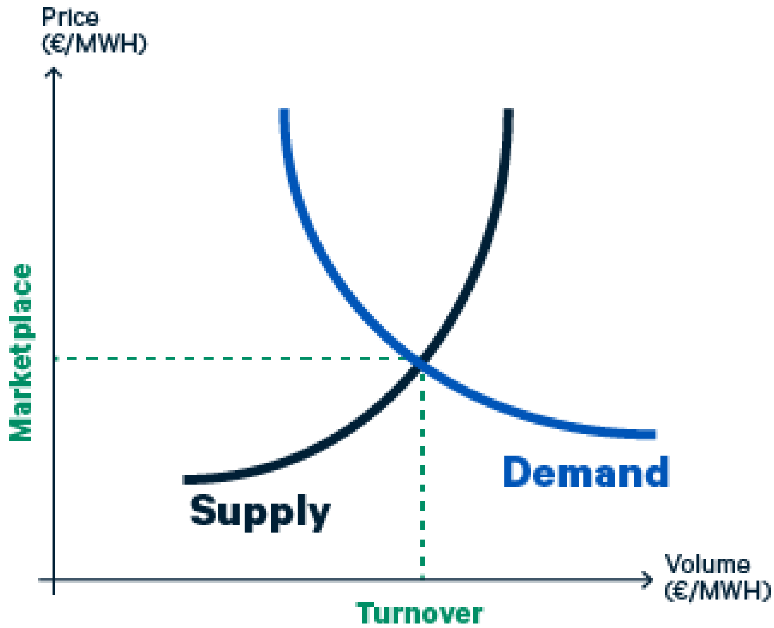

Figure 2. System price computation (Source: www.nordpoolspot.com).

2.1.2 Intraday market

Intraday trading is done in the regulation market. The reason for intraday market is to supplement the Elspot market [13]. Suppose there be any changes that might occur between the closure of day-ahead marketing and power delivery the next trading day. Then intraday trading comes in to ensure there is a balance up between demand and supply in the system. This is made possible since suppliers and retailers have the opportunity to trade close to real time in order to restore the market balance. Setting of prices is based on pay-as-bid basis, one hour to delivery, during the actual trading day [13]. For pay-as-bid, price paid to each generator is dependent on the bid price and this results in all participants having different market prices [14].

2.1.3 Balancing power market

The balancing power market is mainly used when there exists imbalances in the power system, so as to ensure there is a balance between total production and consumption in real time. It is supervised by the transmission system operator (TSO) that is responsible for these operations in the transmission grid. Due to some unforeseen circumstances, producers or consumers might change their original plans, resulting in instability of power in the transmission grid. TSO will have to make necessary adjustments, either on production or consumption depending on the situation at hand. In doing so, TSO accepts bids from the regulating market to allow producers or consumers adjust their original plan so as to induce stability in the transmission grid and balance the market [15]. To increase production, the cheapest up-regulation bid is used first and alternatively the most expensive down-regulating offer is used to decrease production. As a result, prices can be up-regulated or down-regulated. For instance, if electricity prices are published and it happens that on the actual trading day demand is high than predicted, actual electricity load increases in the system. This load leads to a shortage in production and causes the prices to be regulated upwards. On the other hand, if there is more electricity produced than what was initially demanded, there will a surplus in production. Since electricity cannot be stored, prices are lowered so as to be able to supply all what was produced. One possible scenario is illustrated in Figure 3 where the levels of consumption and production need to be adjusted so as to balance the market.

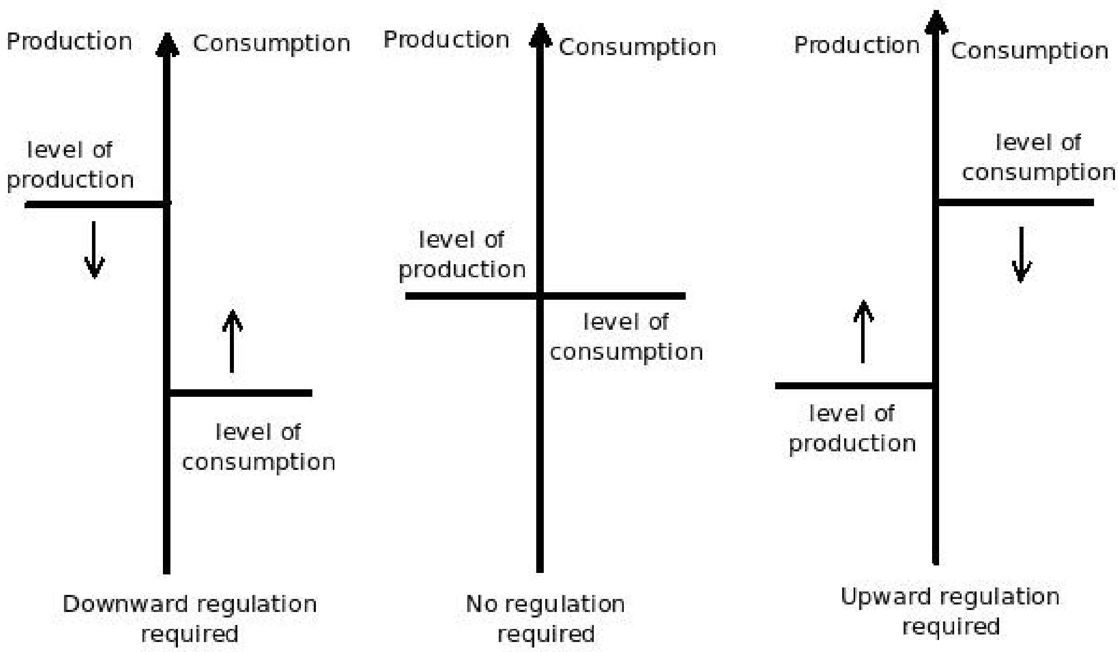

Figure 3. Examples of regulation possibilities

If bids are not strategically set in the spot market, the trading companies or individuals might be forced to go into the regulation market so as to balance up demand and supply and this involves some additional costs. However, to set up bids strategically, traders need to have prior knowledge about the prices and this also helps in reducing and managing risks encountered during the process [6].

2.2 Data description and preliminary visualization

Prices in the Nordic electricity market are affected by a number of factors. Some of these factors include previous or historical prices, weather, predicted power shortages, demand for electricity, generation outages, operational reserves and bidding strategies [6]. Nevertheless, some of these factors are vital while others are not necessarily important. This work is a case study of Finnish electricity market in Nord Pool. The data used is hourly, over a period from 21^{st} May 2016 until 30^{th} April 2017. The missing values in the data were dealt with by replacing them with the previous value in their respective variables.

Electricity spot prices and regulation prices

Prices in the spot and regulating market behave differently. Hourly time series plot for spot prices of Finnish electricity market is displayed in Figure 4 whereas the corresponding regulation price time series plot is displayed in Figure 5.

From Figure 4 and Figure 5, both spot and regulation prices seem not to have a constant mean but behave stochastically with respect to seasons. There are some months that the prices are higher than the rest. Overall, it can be seen that regulation prices are much higher, with many extreme prices compared to the spot prices.

Temperature

Demand for electricity can be affected by weather conditions. If the temperature is too low, more heating will be required in the households and this increases demand for electricity. On the other hand, the higher the temperature, the less heating is required. In bidding for the next trading day, it is necessary that traders have a prior knowledge of the temperature changes. Figure 6 shows the actual temperature on the trading day and the predicted temperature. Temperature levels are suddenly changing throughout the months with heavy changes during winter. On average, both actual and predicted temperatures are high between the months of May and August and very low in January.

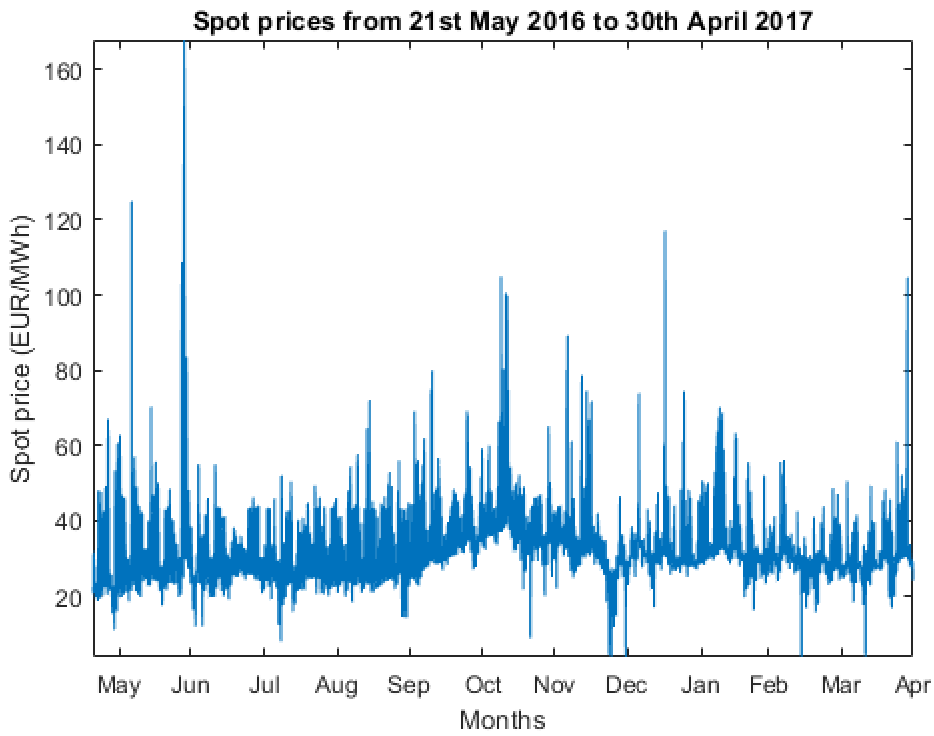

Figure 4. Hourly spot prices

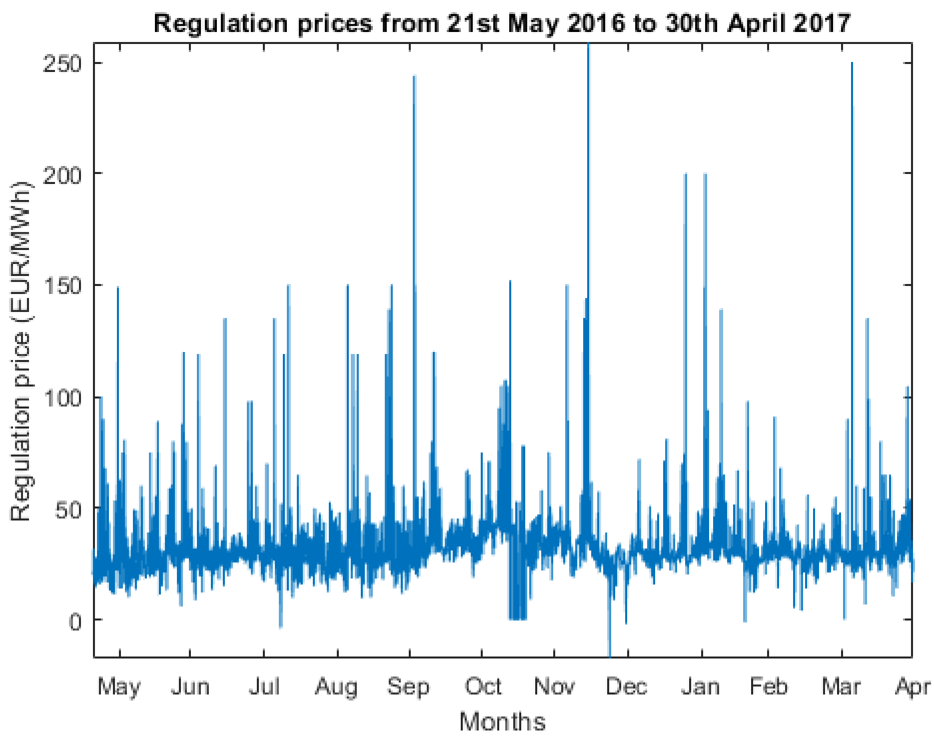

Figure 5. Hourly regulation prices

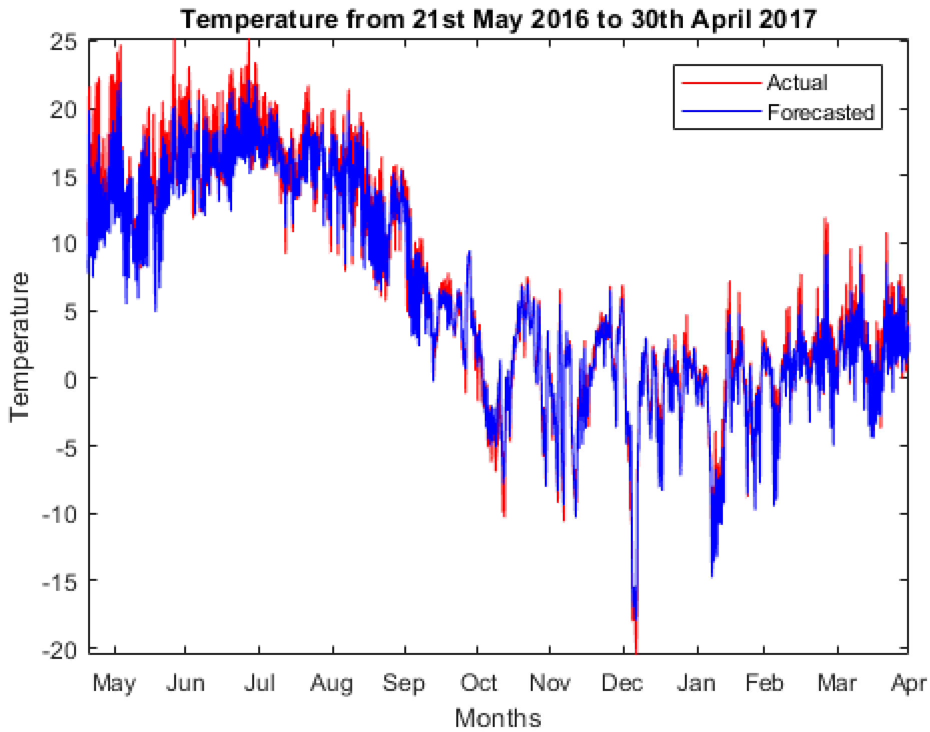

Figure 6. Actual and predicted temperature

Load

Electricity load is associated with different factors such as weather conditions, human social and industrial activities. To ensure there is no overloading in the system and reduce occurrences for failure of the machines, the expected amount of load needs to be known [16]. If there happens to be insufficient load to cater for the demand, an excess provision would be required and the company is entitled to extra costs [17]. Figure 7 is the graphical presentation of actual and predicted load. Overall, there is an increasing trend with minimal extreme values both in actual and predicted load. However, actual load is higher than predicted load.

Production

How much electricity needs to be produced depends on how much is demanded and this helps in strategic bidding and profitable yield. When the temperature is low, there is high production of electricity compared to when the temperature is high which means low levels of temperature demands high levels of production. This is evidently seen in Figure 8 as there is high level of production between the months of December and March. On average, it can be observed that predicted production is low than what was actually produced, with extremely low production in November.

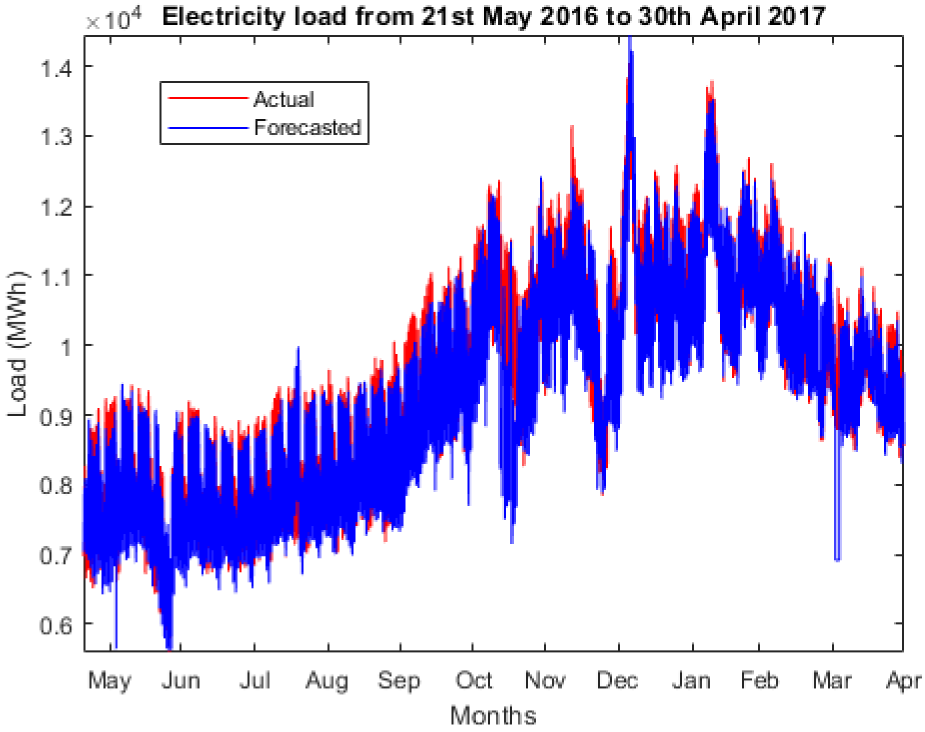

Figure 7. Actual and predicted electricity load

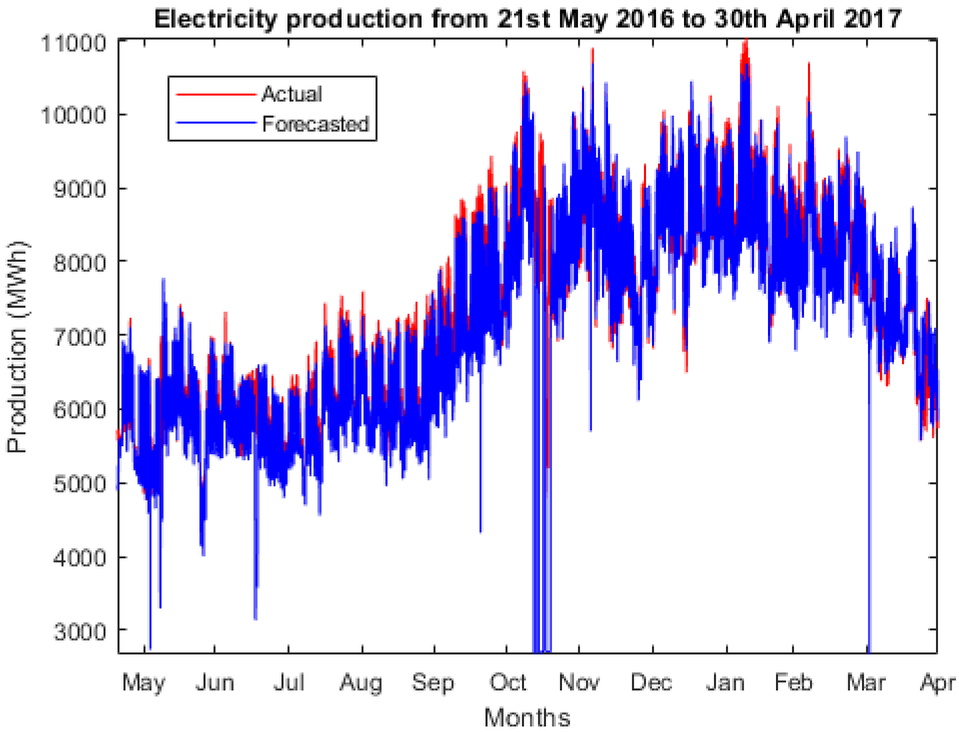

Figure 8. Predicted and actual production

Electricity transmission

The Nord Pool power market is split into several bidding areas. Finland (FI) operates as one bidding area and receives power imported from Norway(NO) and transmitted through Sweden(SE) which was split into four bidding areas in November 2011 [18]. Two Swedish bidding areas SE1 and SE3 transmit power into Finland as shown in Figure 9 which displays the current bidding areas of Nordic power markets.

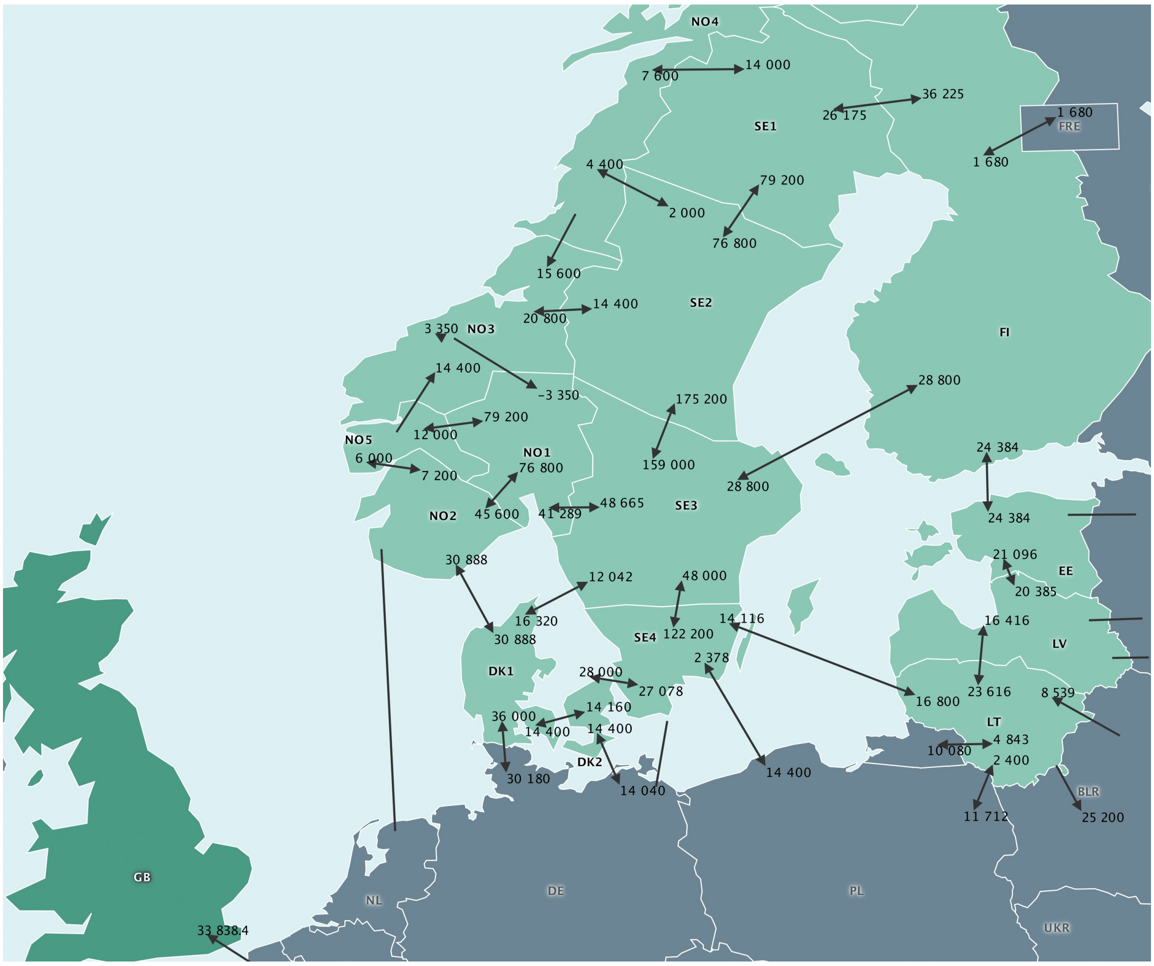

Figure 9. Bidding areas in Nord Pool markets (Source:www.nordpoolgroup.com)

The exchange of power between these cross-border corridors and the sudden fluctuation of electricity prices are influenced by transmission congestion in the grid [19], [7]. Similarly electricity prices are obtained between the cross-border corridors if the transmission capacity between the areas is sufficient and helps inducing competition in the market. The more transmission capacity congestion there is, the more the markets deviate from optimal original production orders and this affects the flow of power in the system [14]. This means that transmission capacity contributes a lot to Nordic electricity prices on the market. The expected transmission (transmission capacity) and what was actually transmitted (transmission commercial) for both SE1 and SE3 into Finland are displayed in Figure 10 and Figure 11 respectively. Transmission capacity between SE3 and FI seems to be lower on average with same transmitted amount for a longer period of time compared to transmission capacity between SE1 and FI. From the Figures, it can also be discovered that there is a big difference between transmission commission and capacity is such way that what was actually transmitted is low than what was expected.

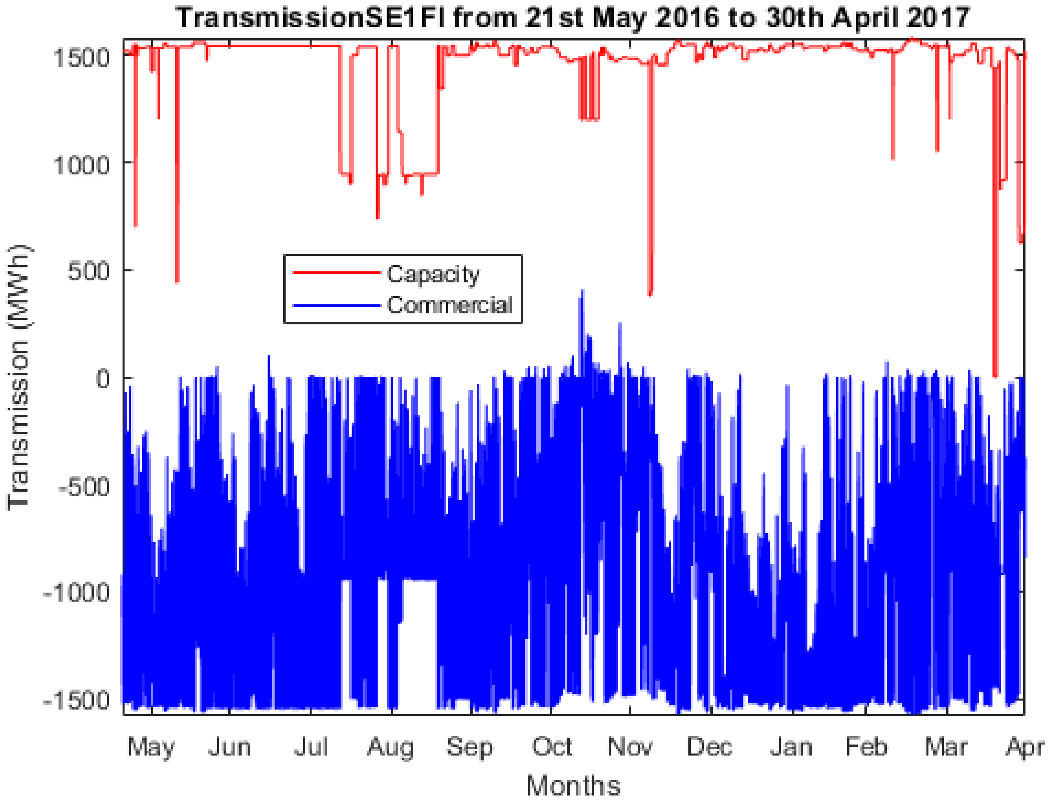

Figure 10. Transmission capacity and transmission commercial for SE1FI

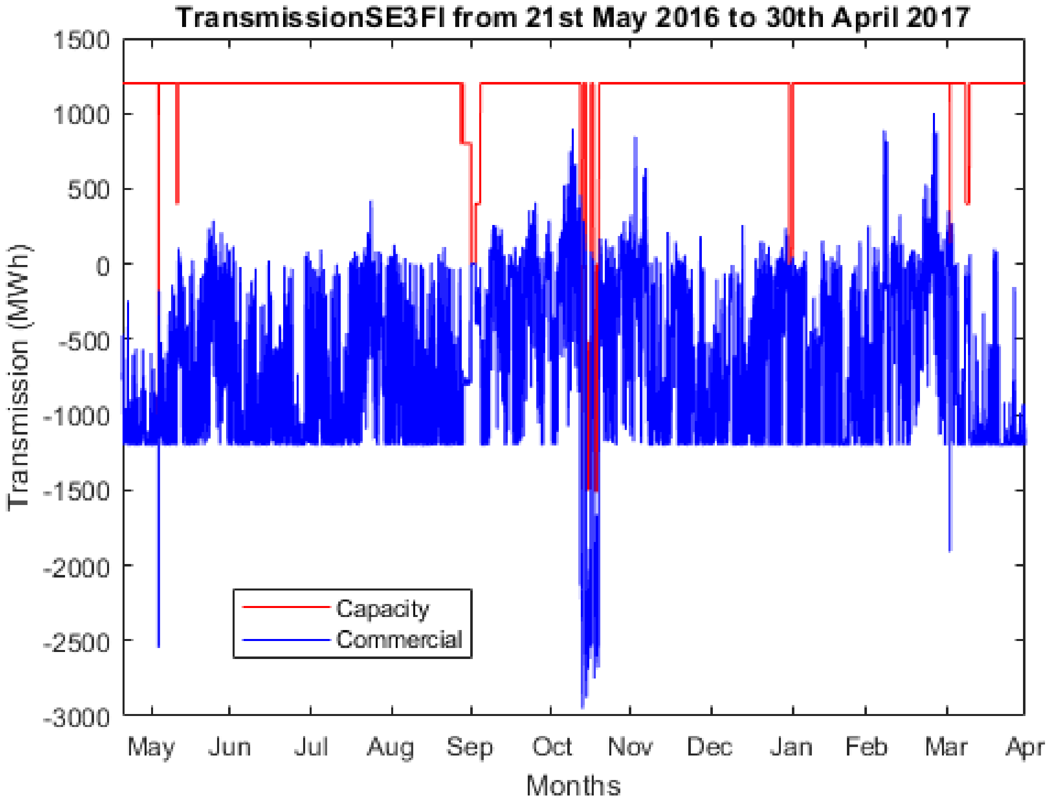

Figure 11. Transmission capacity and transmission commercial for SE3FI

3 NEURAL NETWORK APPROACH TO FORECASTING ELECTRICITY PRICES

Neural networks are a data-driven approach that were originally designed to simulate the activities and functionality of the human brain [20], [21]. What influenced the NN was an attempt to answer some questions that researchers in the fields of artificial intelligence had. Questions like: "*What makes the human brain such a formidable machine in processing cognitive thought? What is the nature of this thing called "intelligence"? And, how do humans solve problems?*" [22]. A solution to these questions is what initiated studies that deal with thought processes that result from an influence having some particular characteristics, to some input senses and then learning from the knowledge that has been acquired by studying such influences.

Recent studies have shown that NN display a powerful performance in a wide variety of tasks in various fields such as business, industry and science [23]. In the field of finance, NN seems to become more popular in forecasting. This is because NN have some unique characteristics such as the ability to handle non-linearity in the data. NN approach can model the behaviour of known systems without specific instructions on the models but simply by learning the relationship directly from the data being modelled. In some tasks, NN outperforms *sophisticated quantitative techniques* as they attain a higher level of accuracy that cannot be achieved by some modelling techniques [24]. They can also tolerate noise in the data and chaotic components better than most methods do [25]. Even though NN gives highly accurate results, there are some inconsistencies that may result due to different methods that are applied by respective researchers. This section briefly discusses the structure of these NN and how they are designed.

3.1 Neural network architecture

A typical NN comprises of three layers: input layer, hidden layer and output layer. Nodes from two successive layers are interconnected with weight that can be modified and also varies according to state of the connection. This weight is associated in the process of training at the entry and exit of the system and together with the network architecture, they store the knowledge that has been trained [25],[26]. In some networks, bias nodes are included in the network for the sake of pattern learning. This kind of a NN is called a feedforward neural network.

3.1.1 Feedforward neural network

In this type of a network, information is transferred directly to the hidden layer from the input layer and then proceeds to the output layer without any cycles or loops included. The general idea about feedforward NN is that inputs from the input layer feed the hidden layer without any feedback given. The nodes in one layer do not feed each other but rather, they feed the nodes in the succeeding layer. Thus, the name feedforward NN since interactions between nodes or feedbacks are involved [27]. An example of feedforward NN is displayed in Figure 12.

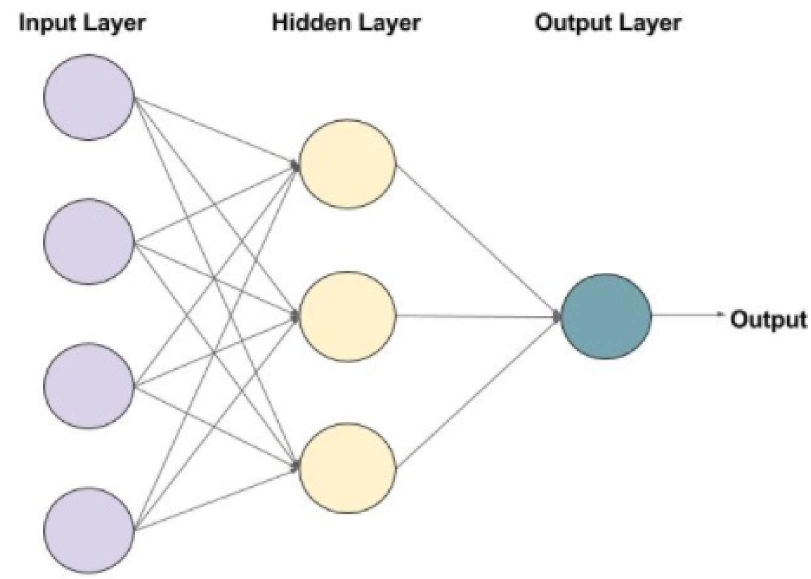

Figure 12. Feedforward neural network (Source: www.learnopencv.com).

The input layer consists of n neurons or nodes that represents n number of explanatory variables that are to be used in modelling a desired output. The hidden layer lies between the input and output layers and is responsible for detection of some features like recognizing the pattern in the data. Execution of complicated non-linear relationships between input and output layers is also performed in the hidden layer. Finally, the output layer which is just a single neuron that corresponds to the value to be predicted [26]. One of the layers that is very vital and complicated to define is the number of neurons to be included in the hidden layer. Much attention is required in assigning the number of hidden nodes. Generally, few nodes are preferable since they have the capacity to make better generalizations as well avoiding over-fitting the data. However, few nodes might not have the sufficient power to learn the data and thus might give poor modelling performance. This is what makes designing a neural network model more of an art than of science [26].

3.2 Backpropagation neural network

One of the classes of a feedforward NN is the backpropagation. This is a procedure that works at minimizing the difference between the actual output (what is returned by the network) and the desired output (which is the fact) by adjusting the weights repeatedly. A signal is sent back to the weights and if this process with adjusted weights is run, the obtained output tends to be closer to the expected or desired output. The whole process of backpropagation is done in three steps which are feedforward of the input observations, back-sending the corresponding error and then finally, adjusting the weight. A brief explanation of how this is done in a three-layer feedfoward NN is described below.

Suppose we denote the input node as X, hidden node as H, W as weight, $\hat{Y}$ as output for the output layer and b the bias. On the onset, each neuron in the input layer receives a signal from the input data which is the respective value at that particular node. This value is fed into the hidden neurons in the hidden layer. The values is then multiplied with the respective weight assigned to each of the nodes and yields

$$K_i = \sum_{i=1}^{n} W_i X_i + b. \tag{1}$$

where $i = 1, 2, 3, \ldots n$ is the number of input variables. This output is compared to the original input value and the error is computed, which is basically the difference between the target value and the output value at this stage. The bias is then fed back into the hidden layer where the weights are updated. This process takes place during the training stage.

Equation (1) is what defines the input at j^{th} hidden node. This value is fed into the activation function, which is the sigmoid function, in the hidden layer. The sigmoid function allows the network to classify the non-linear pattern in the data. Thus, the output at hidden nodes, which automatically becomes the input at output layer nodes, is given in Equation (2).

$$H_j = f(K_i), \tag{2}$$

where $j = 1, 2, 3, \ldots m$ is the size of the hidden layer. Then in the output layer, after the error has been calculated and the weights updated accordingly, we have

$$O_j = \sum_{j=1}^{m} W_j H_j + b. \tag{3}$$

Equation (3) is also fed into a linear activation function which gives the linear combination of these inputs values. Thus, at the output layer, the output is computed as in Equation (4)

$$\hat{Y} = f(O_j). \tag{4}$$

3.3 Levenberg-Marquardt backpropagation (LMB) algorithm

The model has to be trained using the training data set as a way of learning the data. Training the network basically involves estimation of parameters. The main aim for training the network is to obtain network paramaters (weights) that help in making the errors (bias) in the model as small as possible. LMB algorithm is a non-linear least squares algorithm that uses the computed predicted values of the observations and their respected residuals to transform the weights into new values that reduce the sum of squared errors. Details about how this algorithm is implemented can be found in [28], [29]. LMB is one of the training algorithms that is employed in this context as it has a better performance on non-linear regression than other training algorithms [30]. The Matlab function is *trainlm*, which updates the weight and bias in the network using Levenberg-Marquardt optimization [30] with high execution speed.

4 FORECASTING REGULATION PRICES

In order to obtain a forecasting model that has a high prediction performance, independent variables that explain the variability in the response variable need to be adequately determined. It has been noticed that it is the difference between the actual variables and the predicted variables (error of prediction) that makes an influence on the electricity prices. Considering the variables described in section 2.2, it was discovered that for individual variables, only production forecast was correlated with the difference between regulation and spot price. For the difference between the actual and predicted values, only the error of prediction for temperature was not correlated with the price difference. Therefore, the variables we consider in this case study are described as follows:

PriceDiff :	Price difference between regulation and spot price (response variable)
LoadDiff :	Load difference between actual and predicted electricity load
ProdFor :	Production forecast
ProdDiff :	Production difference between actual and predicted electricity production
TrSE1FI :	Difference between transmission capacity and transmission commission of SE1 and FI bidding areas
TrSE3FI :	Difference between transmission capacity and transmission commission of SE3 and FI bidding areas

Figure 13 displays the line plots of the variables used together with their histograms. As already stated, the high volatility in price difference is clearly seen in the time series plots. Price difference, load difference and production difference have a distribution that is skewed to the left. Production forecast seems to be normally distributed and both transmission capacities are skewed to the right.

Figure 14 shows the scatter plots and the correlation between the response and explanatory variables. Load difference and production difference have a negative correlation with the price difference whereas the others show a positive correlation. Production forecast has the highest positive correlation among all other variables.

4.1 Model construction

A feedforward NN with two layers was constructed using the Matlab neural network toolbox. In this study, the NN model that is designed has 5 input variables that are directly connected to neurons in a single hidden layer having 12 neurons and further connected

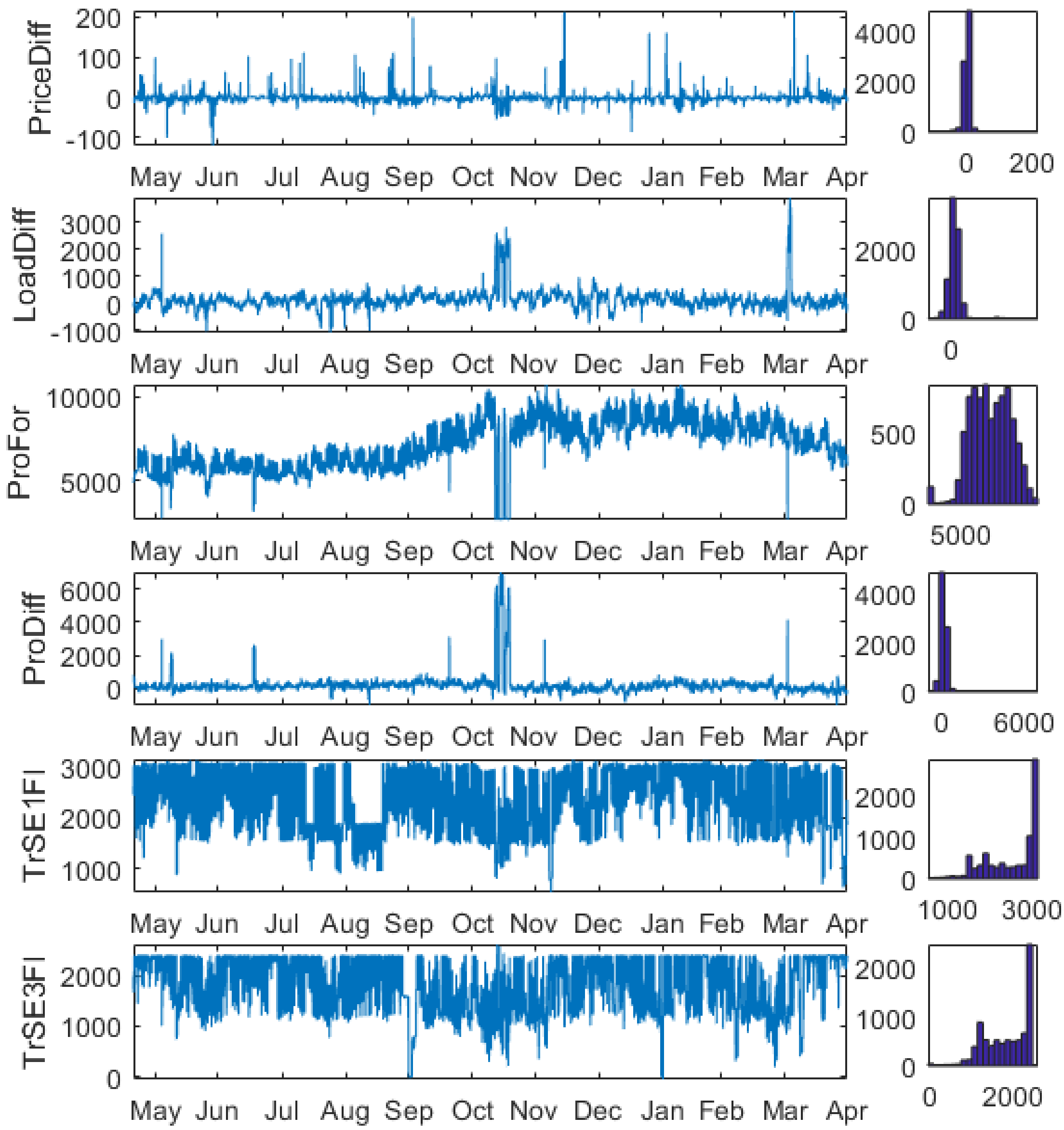

Figure 13. Line plots of the variables

to a single output layer that has a single output. The network has a sigmoid function in the hidden layer and a linear function in the output layer. Figure 15 is the pictorial view of the network constructed. The hidden layer size that produced the best training performance is 12 out of the 20 hidden neurons that were deliberately fed to determine the best number of hidden layers. Data was split into three sets: training, validation and testing data containing 70%, 15% and 15% of the data respectively. The input data was normalized between $[-1, 1]$. This is because of the sigmoid function that is used in a

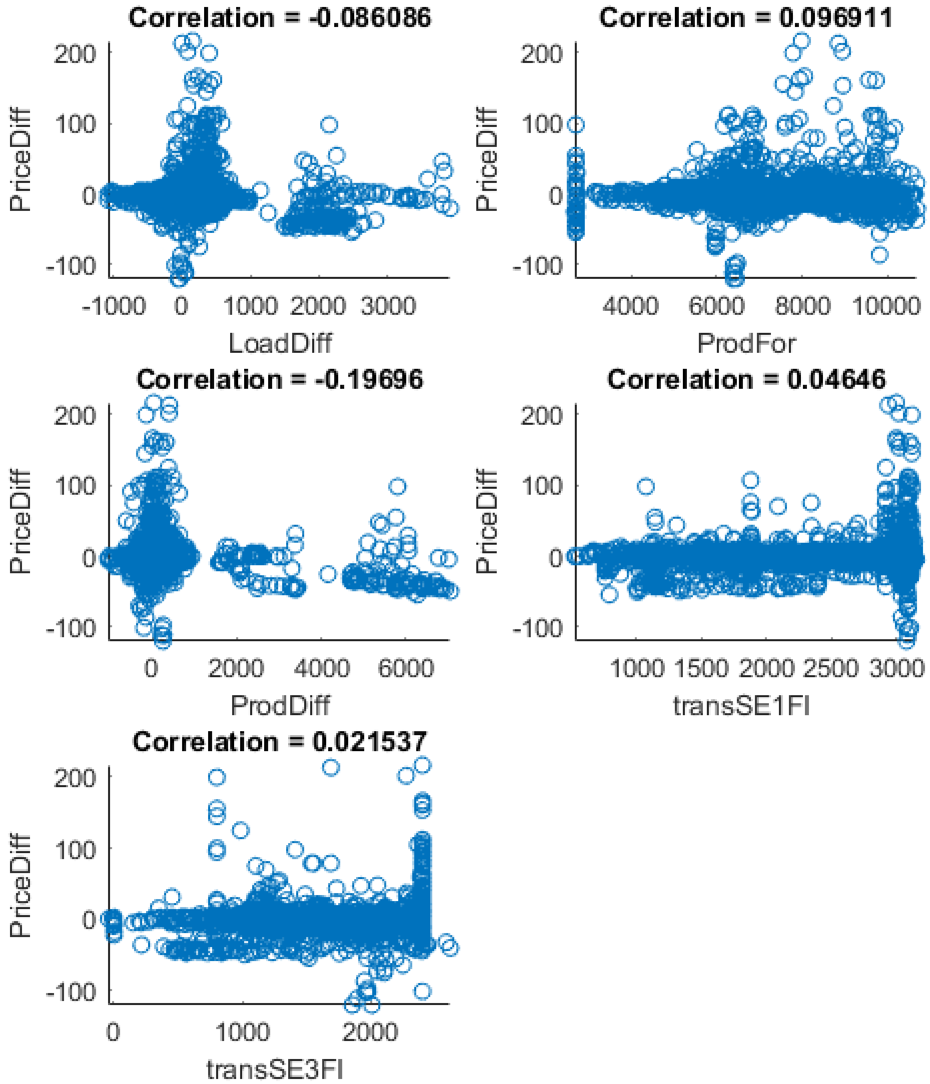

Figure 14. Correlation between response and explanatory variables

supervised network. The advantage is that training becomes more effective and faster [30].

4.2 Regulation price difference

Training the network

Initially, weights are assigned randomly. The idea is that the network starts with a neural network model that is poor in performance and training progresses, the network learns

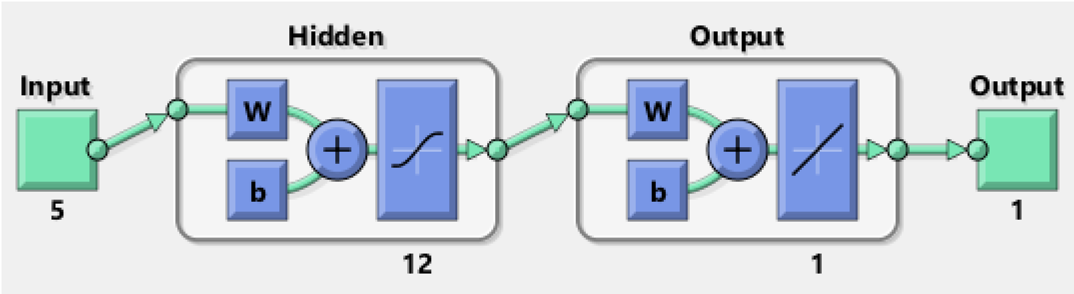

Figure 15. Neural Network Structure

from the data and improves in the network accuracy. In training the data, LMB algorithm in Matlab NN toolbox was used. A summary of the trained state during the training process is shown in Figure 16. It shows that training stopped after 6 validation checks at seventeenth epoch. That is, training continued until the validation error continuously increased for 6 iterations without decreasing. The figure also shows how the gradient magnitude kept on decreasing with respect to increasing the number of epochs. The lower the gradient coefficient, the better the training is [30]. From the trained state plot, there is a decrease in the gradient magnitude with the least value of 164.2228 at epoch 17 which is so small compared to the initial gradient at epoch 0.

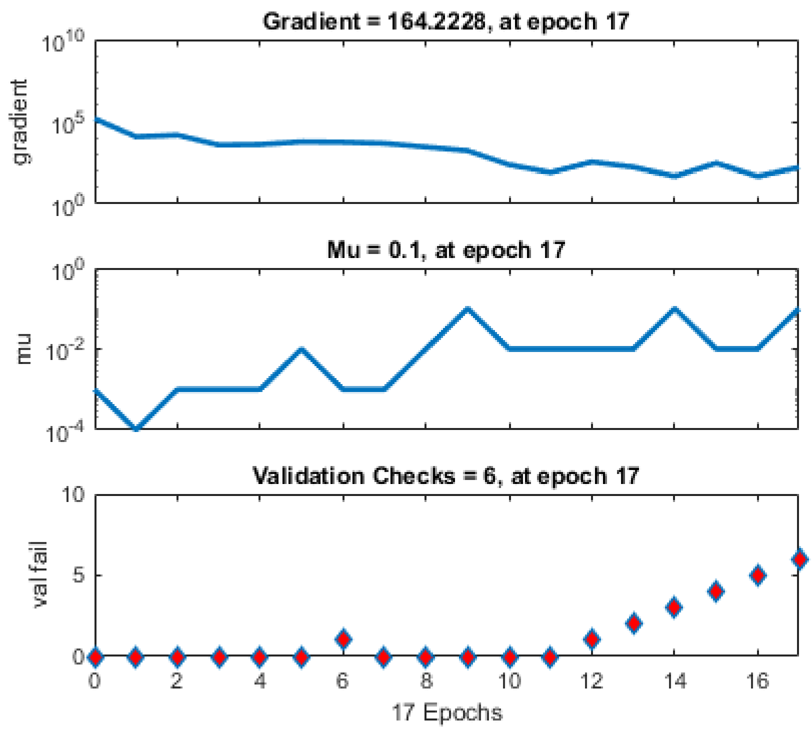

Figure 16. Train state diagram for price difference

For verification of performance of the network, the error histogram displayed in Figure 17 is considered. It appears that majority of the data points are close to the zero error bar. This shows the error between target and input observations is minimal, which is an indication that the network is performing well. There seems to be a smaller percentage of some data points that are a bit further from the zero error bar and they can be considered as extremes. However, we do not consider them as outliers in this case since they are not so different from the rest observations and also they are too minimal to have an impact in the study. Therefore, they are not removed from the sample.

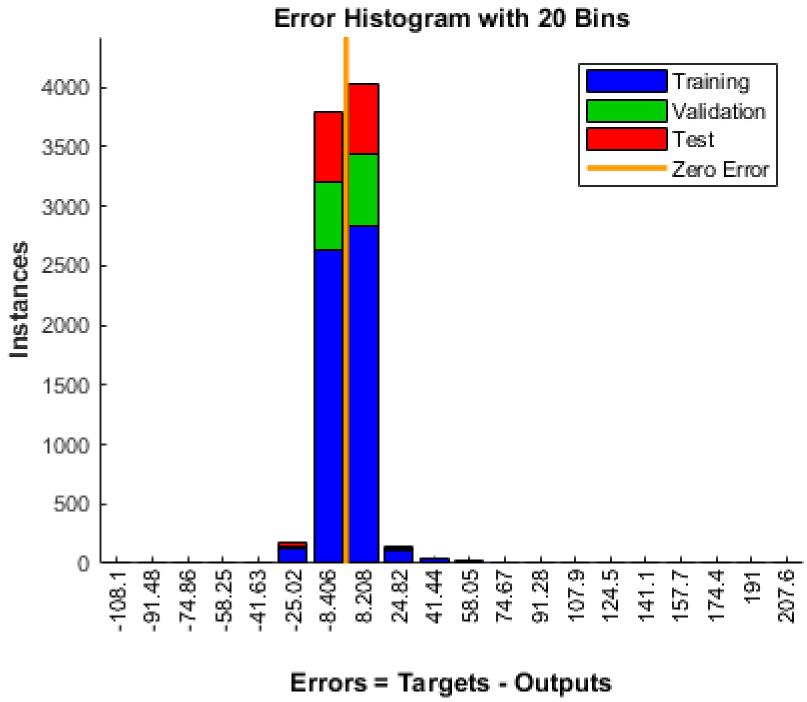

Figure 17. Error histogram for price difference

The best validation performance is 182.0028 at epoch 11, with a reduction in MSE as the number of epochs increases as shown in Figure 18. After eleventh epoch, there is no increase in the MSE for validation state and this gives us an assurance that no over-fitting occurred. It can also be noticed that all the three states MSE display the same characteristics.

Testing the network

After training and validation of the network, the network was used to compute the response for any input values. The network was retrained several times for good accuracy

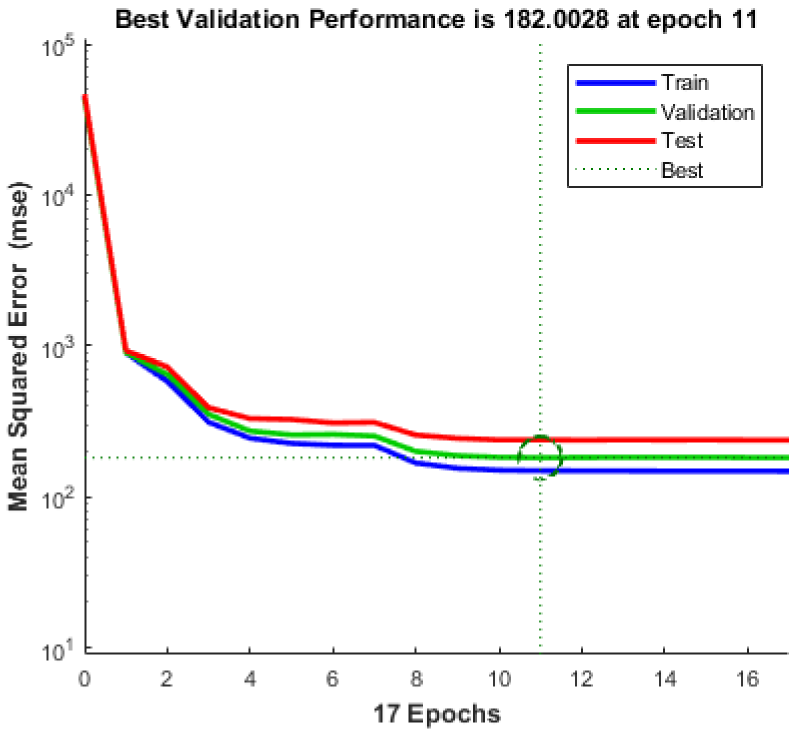

Figure 18. Performance of the Network

of the model performance. Finally, MSE and the overall performance of the network during the testing state were computed. The overall performance calculated was 166.0485.

As an analysis on general performance of the network model, a regression plot for all three states was considered, together with an overall regression plot. From Figure 19 it can be observed that the R value, which is the coefficient of determination, is 0.35064 in the training state which is the highest value out of the three states. The testing state has the value of 0.24296 and finally, the validation state which has a least value of 0.23932. From these results, we argue that the network fits the data even though the R values are considered to be small. The overall goodness of fit is 0.31326, which is accepted in this case due to the type of the data used. Thus, we can say that the model fits the data.

Forecasting using the network

The constructed network was then used to compute the response for the selected inputs. Figure 20 is the result of the predicted price difference together with the original price difference. Having obtained the forecast, we had to check how accurate the predictions are. As discussed in section 4.3, the same procedure was used to transform the predicted price difference into predicted price direction. The ratio of the total sum of the original price direction that are equal to the direction of the predicted price difference to the sum

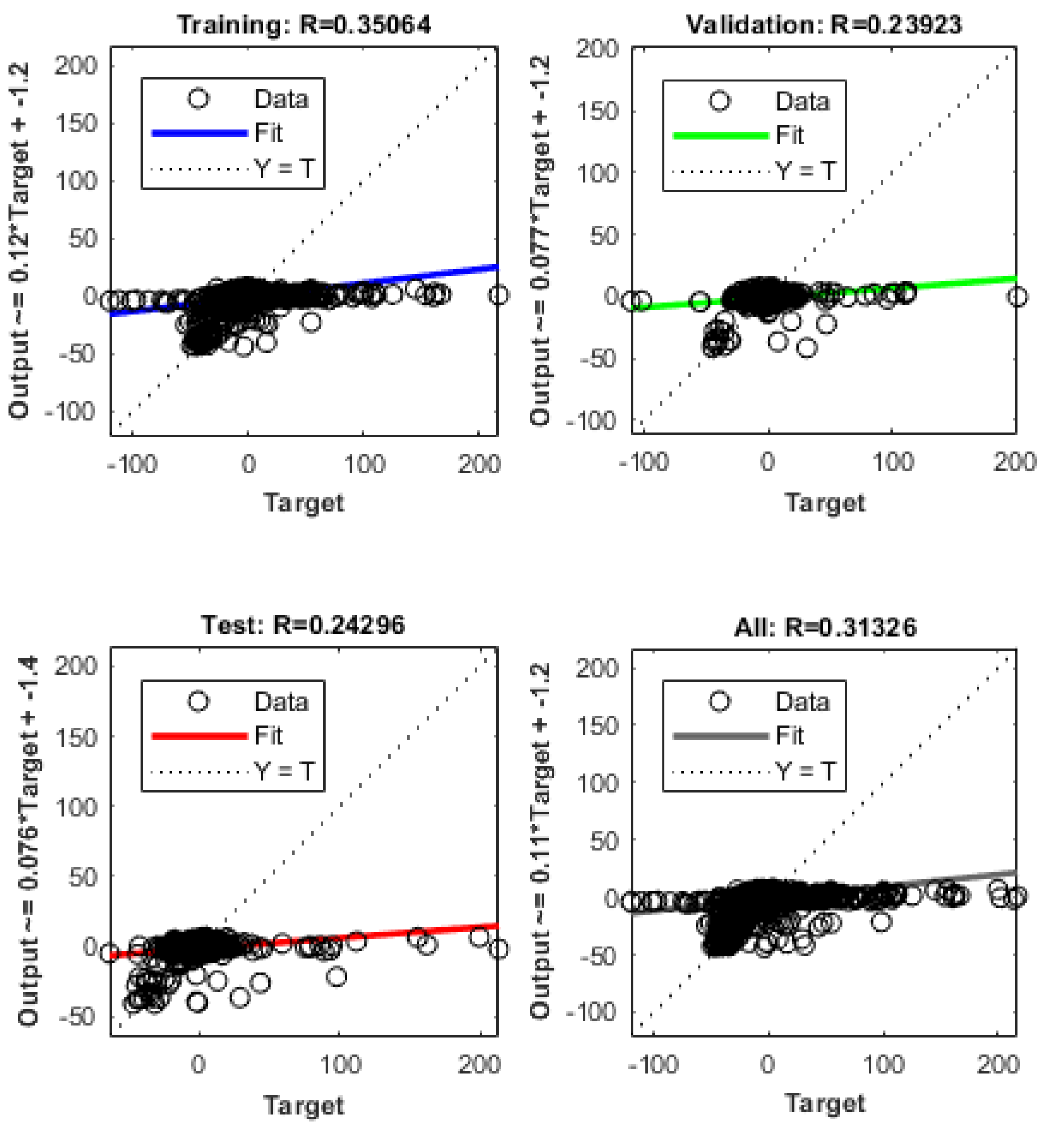

Figure 19. Regression plot with respect to Target

of the size of the price difference was computed. The results obtained show that 0.4401 of the predicted price difference were accurate.

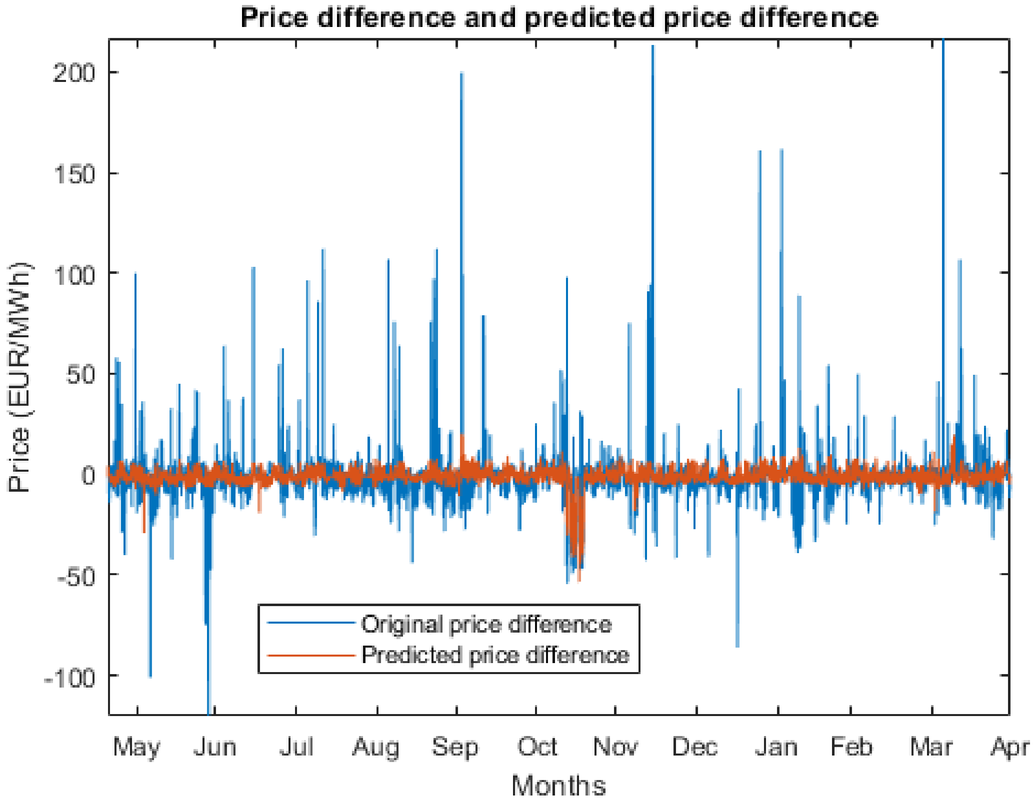

Figure 20. Predicted and original price difference

4.3 Regulation price direction

Since prices can be regulated upwards or downwards, they are bounded in one direction by the spot prices. Therefore, the balancing price which is the target was classified into three categories: when the price difference is negative, positive and zero as $-1, 1$ and 0 respectively. The network was designed in a similar way as the price difference displayed in Figure 15 with the same characteristics.

Training the network

With the classified price difference as the target variable and the rest as input variables, the network was trained. The training state in Figure 21 shows that training stopped after 6 validation checks at epoch 19. As the number of epoch kept on increasing, the gradient magnitude kept on decreasing with the least value of 0.002495 at validation stop. This decrease shows that the network kept on improving in accuracy with respect to the number of epochs.

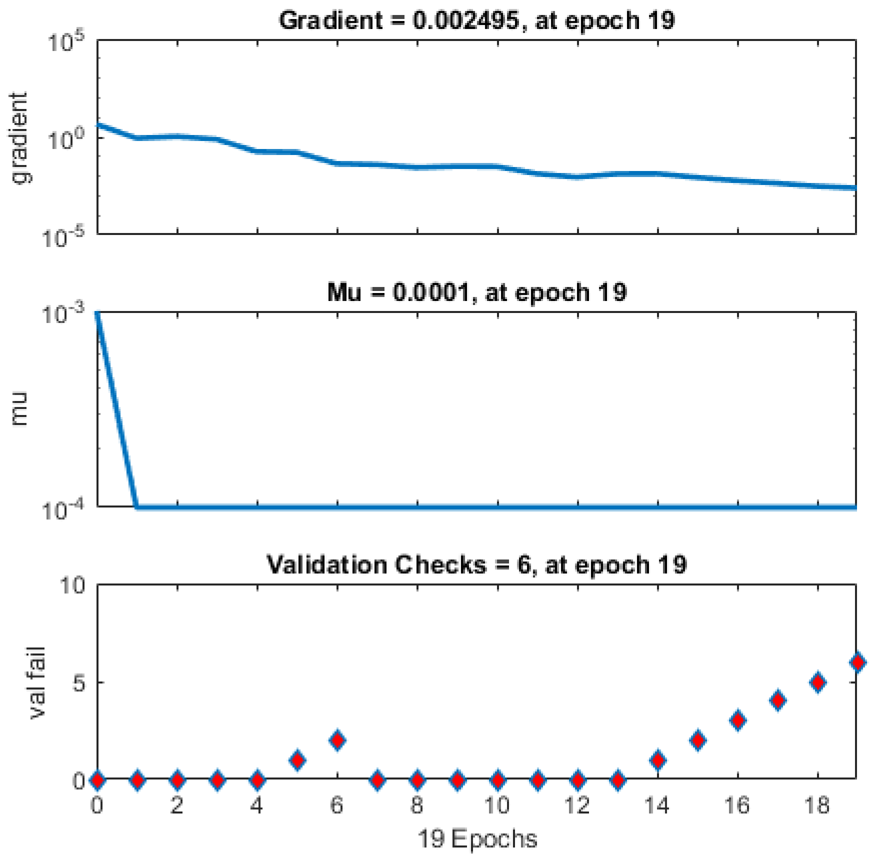

Figure 21. Network training state for price direction

Figure 22 shows the variation of the MSE with respect to number of epochs. There is a decrease in the MSE as the number of epochs increases. Since our aim is to reduce the MSE to be as minimal as possible, Figure 22 displays a decrease in MSE for all the three states. This shows an improvement in the network performance during the training, validation and testing the network. The best fit is thus observed at the thirteenth epoch with a validation performance of is 0.63666.

The error histogram which quantifies the difference between targeted values and the outputs is displayed in Figure 23. The figure indicates that there are almost no observations that show a possibility of insignificant fit compared to all observations since almost all errors are in the range of between -1.388 and 1.441 with only few observations outside this range. These few observations can also be spotted out in the regression plots in Fig-

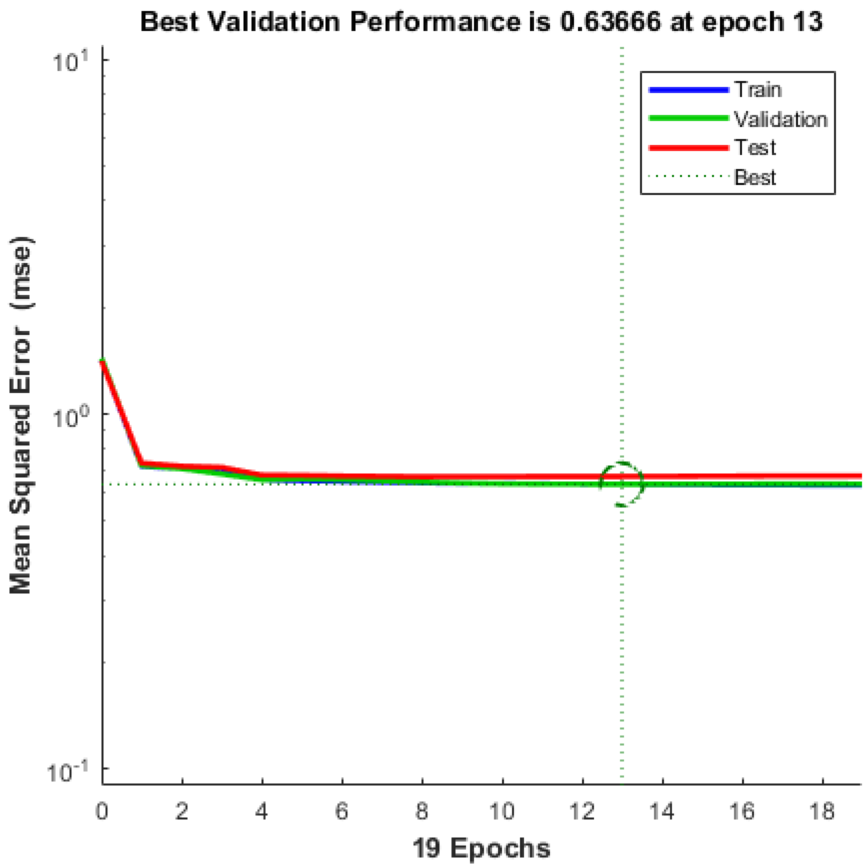

Figure 22. Performance of the Network for price direction

ure 24 which shows the summary of the relation between the target variable against the output variable for all the network states. From Figure 24, it can be seen that coefficients of determination are small for all the states, with the training state having the largest value of 0.28955.

Classification rate

Since the target observations were classified into three classes, we considered the occurrences of the correctly classified values in each class in the training state. Figure 25 is a summary of the results where each correctly and incorrectly classified class is known. The diagonal squares (in green) are the correct responses while off-diagonal (in red) squares are incorrect responses. The percentage of original and predicted observations that are correctly classified in all three class is higher in the first class, with the value 0f 32.0% while the second class has no correctly classified observations. Lastly, the third class has 14.0% of correct classification. In the first output class for the second target class, the confusion matrix shows that 1375 of the observations were incorrectly classified, representing 16.6% percentage of the predicted class. The last rows and columns (in black)

Figure 23. Error histogram for price direction

shows the accuracy for each output and target class respectively with an overall classification occurrence on the lower right square in blue. Therefore, the confusion value, which is the percentage of incorrect classification, is 54.1% as shown in the lower right blue square in red whereas 45.9% of the total observations are correctly classified.

Using the net

The trained network was used to make predictions for the electricity prices. The visual aid of the results is displayed in Figure 26. The results show both upward regulations and downward regulations. However, there are no balanced regulations in the predictions made. This is also evidently seen in the confusion matrix in Figure 25 where there are no correct classifications in the training state for the case where the actual electricity prices are equal to the regulation prices. Overall, the predicted time series show a higher occurrence in the downwards direction compared to upwards regulation.

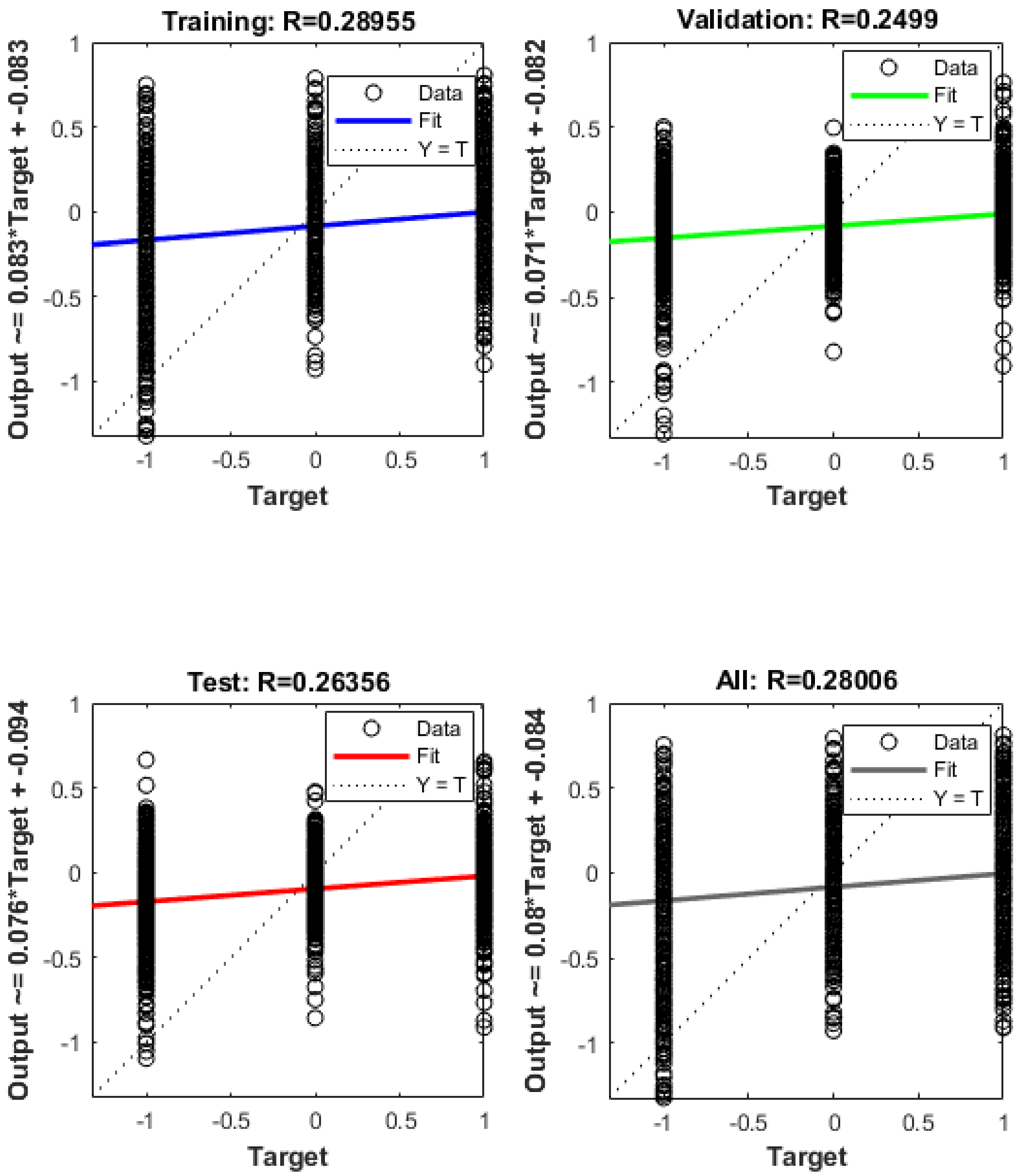

Figure 24. Regression plots for price direction

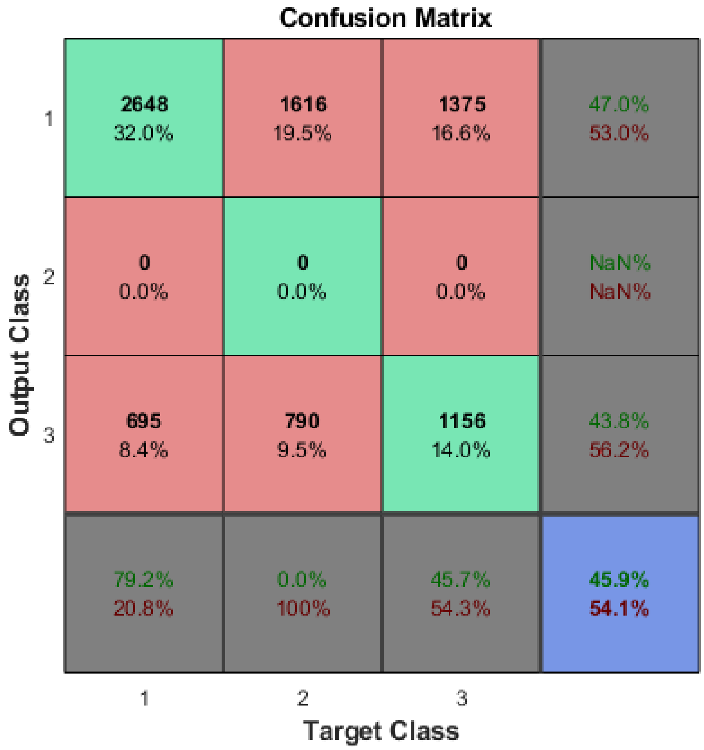

Figure 25. Summary of classification

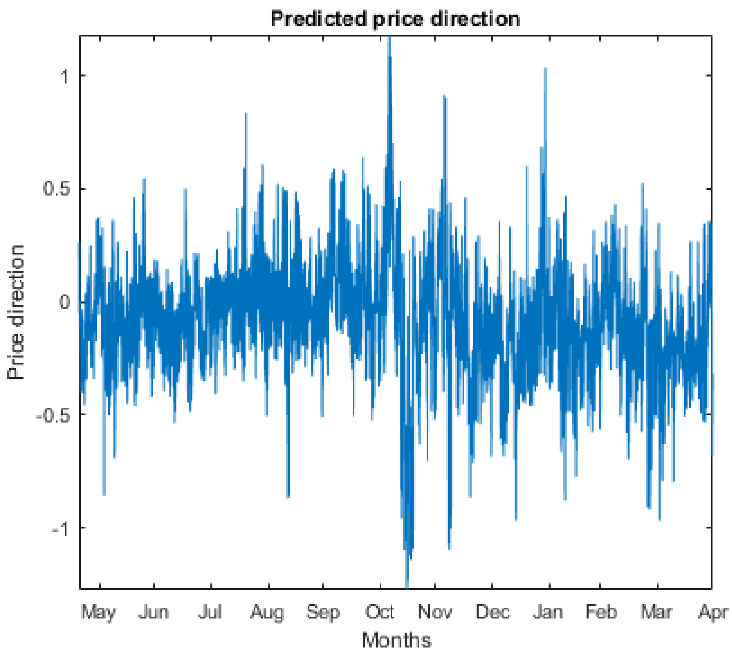

Figure 26. Forecast of balancing price

5 DISCUSSION, CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

This section provides a general discussion on the methodology and the results obtained. Concluding remarks on the obtained results are made and finally, some possible areas for future studies are outlined.

5.1 Discussion

Mainly, the purpose of this study was to forecast electricity prices in the Finnish regulation market. In this study, a forecast for the balancing electricity prices was introduced where the difference between regulation prices and actual electricity prices was modelled using neural networks.

Firstly, a brief discussion on the regulation market was made. The structure of the Nordic electricity markets was presented where we looked into the financial markets at large. The day-ahead, intraday and the balancing power markets were discussed in brief. We discovered that it is not just the actual variables that might have an influence on the market price, but also their predicted variables. This is the case since prices are set upon knowing how much electricity is demanded and to be supplied, and this calls for forecasting the next trading day variables. To predict the balancing electricity prices, variables required were the ones that are said to be correlated with the price difference according to the range of our data set. Therefore, a test for the relation between the price difference and the explanatory variables was done, out of which it was observed that only five variables out of twelve variables were correlated with the targeted variable.

In the first case, prediction of the price difference was carried out. Since theory has it that data normalization speeds up the training process as well as leads to high accuracy, the input data was normalized. In constructing the NN, a large number of hidden layers was deliberately fitted so as to determine the one that that would result in high network performance. The designed model was retrained several times so at to obtain a model with good accuracy. It was discovered that each time the network was being retrained, the output kept on changing. This might be due to the random assignments of weights to the respective nodes. The obtained network was then used to make predictions. From the results we obtained, a NN with twelve hidden layers was the one that had a higher performance. The network was trained using the LMB algorithm and weights were randomly assigned in the input layer. It was discovered that network training yielded fruitful results as the MSE kept on decreasing with an increase in the number of epochs without over-fitting the network. Furthermore, a validation on the network was done. Results showed that the network successfully learned the data as there was a reduction in the MSE and most observations were close to the zero error bar in the error histogram. The last section of network construction involved testing the prediction power of the network, where a few percentage of the observations was reserved for this process. The network was tested and the results also showed that the network was properly structured. The regression fit for all the three states involved in constructing the NN was examined to check how good our model was. The results showed that the coefficient of determination was higher in the training state with the validation state having the least coefficient of determination. We argue that the R-values obtained as displayed in Figure 19 indicate that the model fits the data due to the nature of the data. The obtained network was then used to forecast the price differences. Checking how the fitted model performed, it was discovered that the fit performance was 44.01%. The overall regression fit had a coefficient of determination of 0.31326 which is somehow reasonable according to the type of data.

Next, the idea was to consider the price direction of the balancing prices. The downwards, balanced and upwards regulation were taken into account. The same features of the structured network for the price difference were considered in designing a NN for price direction, where the balancing price direction were the targeted observations. The network was successfully trained. On the onset, the MSE was high but reduced as the number of epochs increased. The gradient magnitude also decreased with an increase in the number of epochs, indicating an improvement in the training performance. Upon validating the network, it was also discovered that the network was properly fitted as there was no overfitting in the fitting process and the MSE reduced with an increase in the epochs' number. Considering the fact that the target observations were split into three classes, a check on the percentage of observations that were correctly classified was considered using the confusion matrix. The results showed that the downward regulation had the highest percentage of correct classification with upward regulation having the least percentage. On the other hand, the confusion matrix showed absence of correct classifications for the balanced regulation. The overall confusion value shows that more than half of the total observations were misclassified with a difference of 8.2% with the correct classification. The fit performance for the balancing/regulation price direction fitted model was 45.9%.

5.2 Conclusions

Based on the results obtained, the models constructed were able to forecast balancing regulation prices and the balancing direction. However, considering the predictability of the model and the type of data used, the predicted prices can be tolerated even though their performance is below 50% in both cases. Since the regulation direction predictions seem to have a higher prediction value than regulation difference, it can be more profitable if traders focus more on whether the prices will be regulated upwards or downwards on the electricity market.

5.3 Future work

This study considered all trading hours and all trading days in this data set. However, we argue that model performance can improve if some factors were taken into consideration. As a possible area for further study, we suggest forecasting using observations in the same hour for the entire data set. That is, we predict the regulation prices for a specific hour in all trading days. Additionally, as discusses in section 2.2, the variables that we thought were of significance in predicting regulation prices fluctuate according to times and seasons. This can also be considered, where the data can be categorized according to their seasons such as winter, summer, spring and autumn. This is because electricity production in winter is very different from that in summer as seen in Figure 7 and Figure 8 where both actual and predicted observations change drastically in winter.

REFERENCES

[1] Hélyette Geman. *Commodities and commodity derivatives: modeling and pricing for agriculturals, metals and energy*. John Wiley & Sons, 2009.

[2] Matylda Jabłonska et al. From fluid dynamics to human psychology. what drives financial markets towards extreme events. *Acta Universitatis Lappeenrantaensis*, 2011.

[3] Nord Pool Spot. The nordic electricity exchange and the nordic model for a liberalized electricity market. *Nord Pool Spot, Norway*, 2009.

[4] Girish Godekere Panchakshara Murthy, Vijayalakshmi Sedidi, Ajaya Kumar Panda, and Badri Narayan Rath. Forecasting electricity prices in deregulated wholesale spot electricity market-a review. *International Journal of Energy Economics and Policy*, 4(1):32, 2014.

[5] Piotr Ptak, M Jabłonska, Dominique Habimana, and Tuomo Kauranne. Reliability of arma and garch models of electricity spot market prices. In *European Symposium on Time Series Prediction, Porvoo, Finland, September 17*, volume 19, pages 21–35, 2008.

[6] JPS Catalão, SJPS Mariano, VMF Mendes, and LAFM Ferreira. An artificial neural network approach for short-term electricity prices forecasting. In *Intelligent Systems Applications to Power Systems, 2007. ISAP 2007. International Conference on*, pages 1–6. IEEE, 2007.

[7] Sergey Voronin and Jarmo Partanen. A hybrid electricity price forecasting model for the finnish electricity spot market. In *The 32st Annual International Symposium on Forecasting, Boston*. Citeseer, 2012.

[8] Klaus Skytte. The regulating power market on the nordic power exchange nord pool: an econometric analysis. *Energy Economics*, 21(4):295–308, 1999.

[9] Tryggvi Jónsson. Forecasting of electricity prices accounting for wind power predictions. Master's thesis, Technical University of Denmark, DTU, DK-2800 Kgs. Lyngby, Denmark, 2008.

[10] Paul L Joskow. Electricity sector restructuring and competition: Lessons learned. *Cuadernos de economía*, 40(121):548–558, 2003.

[11] Torstein Bye and Einar Hope. Deregulation of electricity markets: the norwegian experience. *Economic and Political Weekly*, pages 5269–5278, 2005.

[12] Nord Pool Spot. Day-ahead market, 2017.

[13] Nord Pool Spot. Intraday trading, 2017.

[14] Satu Viljainen, Mari Makkonen, Salla Annala, Dmitry Kuleshov, et al. Vision for european electricity markets in 2030. *Tutkimusraportti/Lappeenrannan teknillinen yliopisto. Teknillinen tiedekunta. LUT Energia*, 2011.

[15] Elsa Kiener. *Analysis of balancing markets*. 2006.

[16] Rafal Weron. *Modeling and forecasting electricity loads and prices: A statistical approach*, volume 403. John Wiley & Sons, 2007.

[17] Samsher Kadir Sheikh and MG Unde. Short term load forecasting using ann technique. *International Journal of Engineering Sciences & Emerging Technologies*, 1(2):97–107, 2012.

[18] Nord Pool Spot. Bidding areas, 2017.

[19] Xin Lu, Zhao Yang Dong, and Xue Li. Electricity market price spike forecast with data mining techniques. *Electric power systems research*, 73(1):19–29, 2005.

[20] Martin S Fridson. Neural networks in finance and investing: Using artificial intelligence to improve real-world performance. *Financial Analysts Journal*, 50(1):77, 1994.

[21] Ricardo Maronna. Alan julian izenman (2008): modern multivariate statistical techniques: regression, classification and manifold learning. *Statistical Papers*, 52(3):733–734, 2011.

[22] Alan Julian Izenman. Modern multivariate statistical techniques. *Regression, classification and manifold learning*, 2008.

[23] Guoqiang Zhang, B Eddy Patuwo, and Michael Y Hu. Forecasting with artificial neural networks:: The state of the art. *International journal of forecasting*, 14(1):35–62, 1998.

[24] Sovan Lek, Marc Delacoste, Philippe Baran, Ioannis Dimopoulos, Jacques Lauga, and Stéphane Aulagnier. Application of neural networks to modelling nonlinear relationships in ecology. *Ecological modelling*, 90(1):39–52, 1996.

[25] Iebeling Kaastra and Milton Boyd. Designing a neural network for forecasting financial and economic time series. *Neurocomputing*, 10(3):215–236, 1996.

[26] Dimitrios Maditinos and Prodromos Chatzoglou. The use of neural networks in forecasting. *Review of Economic Sciences*, 6:161–176, 2004.

[27] J Stuart McMenamin and Frank A Monforte. Using neural networks for day-ahead forecasting. In *Western Economic Association 74th Annual Conference, San Diego*, 1999.

[28] Manolis IA Lourakis. A brief description of the levenberg-marquardt algorithm implemented by levmar. *Foundation of Research and Technology*, 4(1):1–6, 2005.

[29] Martin T Hagan, Howard B Demuth, and Orlando De Jesús. An introduction to the use of neural networks in control systems. *International Journal of Robust and Nonlinear Control*, 12(11):959–985, 2002.

[30] Mark Beale, Martin T Hagan, and Howard B Demuth. Neural network toolbox. *Neural Network Toolbox, The Math Works*, 5:25, 1992.