ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

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PREDICTION OF ELECTRICITY MARKET CLEARING PRICE USING MACHINE LEARNING AND DEEP LEARNING

DEPARTMENT OF COMPUTER ENGINEERING

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ABSTRACT

MASTER THESIS

PREDICTION OF ELECTRICITY MARKET CLEARING PRICE USING MACHINE LEARNING AND DEEP LEARNING

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The market clearing price is the equilibrium monetary value of a traded asset or good and is an important metric in the calculation of electricity prices. In our country, when the electricity price is determined by the companies and in the price changes, market clearing prices are calculated. In this study, forecasting models consisting of 24 forecasts were created in order to make one day forecasts using hourly market clearing price data. The main objective of this thesis is to estimate the market clearing price of electricity using Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM), which are machine learning and deep learning methods and to create appropriate models. The performance of the predicted models was evaluated by calculating the Mean Absolute Percent Error (MAPE) value. The results generally show that LSTM (Long Short Term Memory) and CNN (Convolutional Neural Network) based models perform better than other methods.

Keywords: Machine and Deep Learning, Forecast, Market Clearing Price

ÖZ

YÜKSEK LİSANS TEZİ

MAKİNE ÖĞRENME VE DERİN ÖĞRENME YÖNTEMLERİ KULLANILARAK ELEKTRİK PİYASA TAKAS FİYATININ TAHMİNİ

Abdulhalim YANAR

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Piyasa takas fiyatı işlem gören bir varlığın veya malın denge parasal değeridir ve elektrik fiyatlarının hesaplanmasında da önemli bir metriktir. Ülkemizde de firmalar tarafından elektrik fiyatı belirlenirken ve oluşacak fiyat değişimlerinde, piyasa takas fiyatları hesaplanır. Bu çalışmada, saatlik piyasa takas fiyatı verileri kullanılarak bir günlük tahminler yapabilmek amacıyla 24 adet tahminlerden oluşan tahmin modelleri oluşturuldu. Bu tezin temel amacı, makine öğrenimi ve derin öğrenme yöntemlerinden Çok Katmanlı Algılayıcı (Multilayer Perceptron, MLP), Tekrarlayan Nöral Ağ (Recurrent Neural Network, RNN), Konvolüsyonel Sinir Ağı (Convolutional Neural Network, CNN) ve Uzun Kısa Süreli Bellek (Long Short Term Memory, LSTM) kullanarak elektriğin piyasa takas fiyatını tahmin etmek ve buna uygun modeller oluşturmaktır. Oluşturulan tahmin modellerin performansı Ortalama Mutlak Yüzde Hata (Mean Absolute Percentage Error, MAPE) değeri hesaplanarak değerlendirilmiştir. Sonuçlar, genel olarak Uzun Kısa Süreli Bellek (Long Short Term Memory, LSTM) ve Konvolüsyonel Sinir Ağı (Convolutional Neural Network, CNN) tabanlı modellerin diğer yöntemlerden daha iyi performans elde ettiğini göstermektedir.

Anahtar Kelimeler: Makine ve Derin Öğrenme, Tahmin, Piyasa Takas Fiyatı

EXTENDED ABSTRACT

Rapid development is observed in the electricity and energy market in Turkey. The competition in the electricity and energy markets and the determination of the electricity prices of the companies are of great importance. Market clearing in economics is the process in which the supply of trading in any economic market is equal to the demand. In this direction, clearing price is the equilibrium monetary value of a traded asset or good. PTF formed in the day-ahead electricity market is one of the most important parameters in determining the price of electricity and estimating the price of electricity. This price is determined by the bid-ask process of buyers and sellers, prices always adjust up or down and these also apply to the electricity market. Therefore, estimating market clearing prices for price changes is very important for electricity producers and electricity distribution companies in the market. In this process, accurate estimation of the market clearance price plays an important role in creating the supply-demand balance. While electricity prices are determined by companies in our country, production, demand and market clearing prices are calculated. Therefore, the resulting prices have made the forecast of market clearing prices, which can be foreseen before, very important.

There are different studies in the literature on market clearing price estimation. In studies conducted to date, it is seen that the general market clearing price estimate is not sufficient. Research and results related to this issue reveal the necessity of creating new prediction models and making prediction models more accurate and developing new prediction models accordingly.

Today, it is very popular to use machine and deep learning methods in predicting the future. In this thesis, the market clearing price of electricity is estimated by using machine learning and deep learning methods.

The main objective of this thesis is to estimate the market clearing price of electricity using Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM),

which are machine learning and deep learning methods and to create appropriate models. In this thesis, market clearing price data sets was used for the prediction attempts the period of 01.01.2016 to 01.01.2018. Datasets have been provided from (https://seffaflik.epias.com.tr) website. The performance of machine learning and deep learning methods used were compared and evaluated by calculating the Mean Absolute Percent Error (MAPE) value.

This software contains some basic parameters of artificial neural networks produced using machine learning and deep learning methods. These parameters play an important role in the creation of artificial neural networks and significantly affect the results of artificial neural networks. In this study, parameters such as hidden layer size, time delays, number of periods and hidden units have been optimized in artificial neural networks, thus increasing the efficiency of artificial neural networks. Machine learning and deep learning methods used in this thesis, time series analysis was used to forecast future values. The values in the data set consist of time-acquired data and time delays are effectively used for methods. Time lag in time series forecast is a parameter used in time series analysis. It is usually obtained by shifting the data as necessary. In this thesis, the autocorrelation values of the data sets were calculated using the delay values.

Autocorrelation in data sets is an important element in time series. Autocorrelation can be expressed as the correlation between any time shift and itself. In this thesis, feedback delays, one of the optimizations applied to the neural network, are established by using autocorrelation values.

Using the market price clearing database, 24 forecasts were made and forecasting models were produced based on time delays and autocorrelation values. In the generated estimation models, learning has been made by increasing the parts of the dataset from the last 500 to 1500 by 100. The prediction models developed contain parameters appropriate to the machine and deep learning method whichever machine and deep learning method was used. Different error rates were obtained by

using time delay and autocorrelation values. 66 tables and 594 different models were produced from prediction models.

The average MAPE values obtained while optimizing the time delays used in the applied MLP, LSTM, CNN and RNN machine and deep learning methods ranged between 15.97 and 18.31. These two values were obtained when the autocorrelation threshold was greater than 0.8 and the autocorrelation values were from 1 to 25. The mean MAPE values obtained for LSTM ranged between 9.49 and 11.72, and these two values were obtained when the autocorrelation threshold was greater than 0.8 and the autocorrelation values were from 1 to 25. The mean MAPE values obtained for CNN ranged between 5.06 and 6.51, and these two values were obtained when the autocorrelation threshold was greater than 0.9 and the top 10 autocorrelation values were used. The mean MAPE values obtained for RNN ranged between 18.67 and 25.11, and these two values occurred when the top 10 autocorrelation values were used and the autocorrelation threshold was greater than 0.9. Based on these results, the lowest mean MAPE value obtained from prediction models was 5.06 and obtained from CNN method, and the highest mean MAPE value was 25.11 and obtained from the RNN method.

The average MAPE obtained from CNN and LSTM based forecasting models has a lower average MAPE value than other applied machine learning and deep learning methods when evaluated based on the average MAPE results obtained from market clearing price estimates. The values obtained from the market clearing price estimates based on the average MAPEs based on their performances are 5.82 for CNN, 10.54 for LSTM, 17.25 for MLP and 21.77 for RNN, respectively. The ranking of the applied machine learning and deep learning methods in terms of performance considering the average lowest MAPEs can be evaluated as CNN, LSTM, MLP and RNN for market clearing price estimation. According to these results, it is vitally important which machine and deep learning method will be used to make the most accurate prediction and develop the most accurate prediction models.

When the average MAPE values obtained are evaluated, it is observed that the amount of teaching used from the highest performances dataset is different. Therefore, the amount of learning to be used in the dataset has been proved to be a very important parameter in order to obtain more stable and lower error rates than the prediction models. According to the results obtained from the models, it has been proved that the LSTM, MLP, CNN and RNN machine and deep learning methods can be used in an acceptable degree of accuracy of the electricity market clearing price.

GENİŞLETİLMİŞ ÖZET

Türkiye'de elektrik ve enerji piyasasında hızlı bir gelişim gözlenmektedir. Elektrik ve enerji piyasasında görülen rekabetle birlikte firmaların elektrik fiyatlarının belirlenmesi büyük önem arz etmektedir. Ekonomide, piyasa takas olarak adlandırılan işlem gören arzın herhangi bir ekonomik piyasada talebe eşit olduğu süreçtir. Bu doğrultuda, piyasa takas fiyatı işlem gören bir varlığın veya malın denge parasal değeridir. Gün öncesi elektrik piyasasında oluşan PTF, elektriğin fiyatının belirlenmesinde ve elektrik fiyatının tahmin edilmesinde en önemli parametrelerden biridir. Bu fiyat, alıcı ve satıcıların teklif isteme süreci ile belirlenir ve fiyatlar her zaman yukarı veya aşağı yönde ayarlanır. Bununla birlikte belirlenen fiyatlar da elektrik piyasasına uygulanır. Bu nedenle, fiyat değişimleri için piyasa takas fiyatlarını doğru tahmin etmek piyasada elektrik üretici ve elektrik dağıtımı yapan şirketler için çok önemlidir. Bu süreçte piyasa takas fiyatını doğru tahmin etmek, arz talep dengesinin kurulmasında da önemli bir rol oynamaktadır. Ülkemizde firmalar tarafından elektrik fiyatı belirlenirken, üretim, talep ve piyasa takas fiyatları hesaplanır. Bu nedenle, ortaya çıkacak fiyatlar daha önce öngörülebilecek piyasa takas fiyatlarının tahminini çok önemli hale getirmiştir.

Literatürde piyasa takas fiyatı tahmini üzerine yapılmış farklı çalışmalar bulunmaktadır. Bugüne kadar yapılan çalışmalarda genel olarak piyasa takas fiyatı tahmininin yeterli miktarda olmadığı görülmektedir. Bu konu ile ilgili yapılan araştırmalar ve alınan sonuçlar yeni tahmin modellerinin oluşturulması ve tahmin modellerinin daha doğru tahminler yapması ve buna uygun yeni tahmin modellerinin geliştirilmesi gerekliliğini ortaya çıkarmaktadır.

Günümüzde geleceğe yönelik yapılan tahminlerde makine ve derin öğrenme yöntemlerinin kullanılması oldukça popülerdir. Bu tezde, makine öğrenimi ve derin öğrenme yöntemlerini kullanarak elektriğin piyasa takas fiyatı tahmini yapılmıştır.

Bu tezin temel amacı, makine öğrenimi ve derin öğrenme yöntemlerinden Çok Katmanlı Algılayıcı (Multilayer Perceptron, MLP), Tekrarlayan Nöral Ağ

(Recurrent Neural Network, RNN), Konvolüsyonel Sinir Ağı (Convolutional Neural Network, CNN) ve Uzun Kısa Süreli Bellek (Long Short Term Memory, LSTM) kullanarak elektriğin piyasa takas fiyatını tahmin etmek ve buna uygun yeni modeller oluşturmaktır. Tez çalışması boyunca geliştirilen tahmin modellerinde 01.01.2016 - 01.01.2018 dönemi piyasa takas fiyatı veri seti kullanılmıştır. Veriseti Türkiye'de Enerji Piyasaları İşletme A.Ş (EPİAŞ) tarafından PTF fiyatlarının yayımlandığı (https://seffaflik.epias.com.tr) web sitesinden sağlanmıştır. Kullanılan makine öğrenimi ve derin öğrenme yöntemlerinin performansı ortalama mutlak yüzde hata (MAPE) değerleri hesaplanarak karşılaştırılmış ve değerlendirilmiştir.

Makine öğrenimi ve derin öğrenme yöntemleri kullanılarak üretilen yapay sinir ağları bazı temel parametreler içermektedir. Bu parametreler yapay sinir ağlarının oluşturulmasında önemli bir yer tutmaktadır ve yapay sinir ağlarının sonuçlarını önemli ölçüde etkiler. Bu çalışmada da gizli katman boyutu, zaman gecikmeleri, dönem sayısı ve gizli birimler gibi parametreler yapay sinir ağlarında optimize edilmiş, böylece yapay sinir ağlarının verimliliği artırılmıştır. Tezde kullanılan makine öğrenimi ve derin öğrenme yöntemleri, gelecekteki değerleri tahmin etmek için zaman serileri analizi kullanılmıştır. Veri setindeki değerler zamandan elde edilen verilerden oluşur ve zaman gecikmeleri yöntemler için etkin bir şekilde kullanılır. Zaman serisi tahmindeki zaman gecikmesi, zaman serisi analizinde kullanılan bir parametredir. Genellikle verilerin gerektiği gibi kaydırılmasıyla elde edilir. Bu tezde, veri kümelerinin otokorelasyon değerleri gecikme değerleri kullanılarak hesaplanmıştır.

Veri kümelerinde otokorelasyon zaman serilerinde önemli bir unsurdur. Otokorelasyon, herhangi bir zaman kayması ile kendisi arasındaki korelasyon olarak ifade edilebilir. Bu tezde, sinir ağına uygulanan optimizasyonlardan biri olan geri besleme gecikmeleri otokorelasyon değerleri kullanılarak tespit edilmiştir.

Piyasa fiyat takası veriseti kullanılarak 24 adet tahminlerde bulunulmuş ve zaman gecikmeleri ve otokorelasyon değerleri baz alınarak tahmin modelleri üretilmiştir. Üretilen tahmin modellerinde verisetinin son 500'den 1500'e kadara olan kısımları 100'er arttırılarak öğrenme yapılmıştır. Geliştirilen tahmin modelleri hangi makine ve derin öğrenimi yöntemi kullanıldıysa o makine ve derin öğrenimi yöntemine uygun parametreler içermektedir. Geliştirilen tahmin modelleri zaman gecikmeleri ve otokorelasyon değerleri kullanılarak farklı hata oranları elde edildiği görülmüştür. Tahmin modellerinden 66 tablo ve 594 farklı model üretilmiştir.

Uygulanan MLP, LSTM, CNN ve RNN makinesinde kullanılan zaman gecikmeleri ve derin öğrenme yöntemleri optimize edilirken elde edilen ortalama MAPE değerleri, MLP'de 15.97 ve 18.31 arasında değişmektedir. Bu iki değer otokorelasyon değeri 0.8'den büyük olduğunda ve 1'den 25'e kadar otokorelasyon değerine sahip olduğunda elde edilmiştir. LSTM için elde edilen ortalama MAPE değerleri 9.49 ve 11.72 arasında değişmektedir. Bu iki değer otokorelasyon eşiği 0.8'den büyük ve otokorelasyon değerleri 1'den 25'e kadar olduğunda hesaplanmıştır. CNN için elde edilen ortalama MAPE değerleri 5.06 ve 6.51 arasında değişmektedir. Bu iki değer, otokorelasyon değerleri otokorelasyon eşiği 0.9'dan büyük ve en iyi 10 otokorelasyon değeri kullanıldığında elde edilmiştir. RNN için elde edilen ortalama MAPE değerleri 18.67 ile 25.11 arasında değişmektedir. Bu iki değer otokorelasyon değerleri en iyi 10 otokorelasyon değeri kullanıldığında ve otokorelasyon değerleri 0.9'dan büyük olduğunda meydana gelmiştir. Bu sonuçlara dayanarak, tahmin modellerinden elde edilen en düşük ortalama MAPE değeri CNN yönteminden elde edilen 5.06'dır ve en yüksek ortalama MAPE değeri RNN yönteminden elde edilen 25.11'dir.

CNN ve LSTM tabanlı tahmin modellerinden elde edilen ortalama MAPE değerlerinin, piyasa takas fiyat tahminlerinden elde edilen ortalama MAPE sonuçlarına göre değerlendirildiğinde, uygulanan diğer makine öğrenimi ve derin öğrenme yöntemlerinden daha düşük bir ortalama MAPE değerine sahiptir. Piyasa takas fiyat tahminlerinden elde edilen ve performanslarına göre ortalama MAPE'lerin değerleri LSTM için 10.54, MLP için 17.25, RNN için 21.77 ve CNN için 5.82'dir. Uygulanan makine öğrenimi ve derin öğrenme yöntemlerinin piyasa takas fiyatı üzerinde yapılan tahminlerinden elde edilen ortalama en düşük

MAPE'leri dikkate alarak performans açısından sıralaması CNN, LSTM, MLP ve RNN olarak değerlendirilebilir. Bu sonuçlara göre, en doğru tahmini yapmak ve en doğru tahmin modellerini geliştirmek için hangi makine ve derin öğrenme yönteminin kullanılacağı hayati önem taşımaktadır.

Elde edilen ortalama MAPE değerlerine göre geliştirilen tamin modelleri değerlendirildiğinde, en yüksek performanslar veri setinden kullanılan öğretme miktarlarının farklı olduğu gözlenmektedir. Bu yüzden tahmin modellerinden daha kararlı ve daha düşük hata oranları elde etmek için veri kümesinde kullanılacak öğrenme miktarlarının çok önemli bir parametre olduğu kanıtlanmıştır. Modellerden elde edilen sonuçlara göre, elektrik piyasa takas fiyatının kabul edilebilir bir doğruluk derecesinde LSTM, MLP, CNN ve RNN makine ve derin öğrenme yöntemlerinin kullanılabileceği kanıtlanmıştır.

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LIST OF ABBREVIATIONS

MLP : Multilayer Perceptron
RNN : Recurrent Neural Network
CNN : Multilayer Perceptron
LSTM : Long Short Term Memory
A.C. : Autocorrelation
MAPE : Mean Absolute Percentage Error

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1. INTRODUCTION

1.1. Overview of Market Clearing Price

Due to the technological developments in our age, the production and use of electrical devices has increased rapidly, and the predetermined price of electricity has become an important factor in the behavior of supply and demand firms in the market.

Market clearing in economics is the process in which the supply of trading in any economic market is equal to the demand. In this direction, clearing price is the equilibrium monetary value of a traded asset or good. This price is determined by the bid-ask process of buyers and sellers, prices always adjust up or down and these also apply to the electricity market. The electricity prices, which are determined before the electricity generation and consumption is introduced to the market, are called the market clearing price.

Market clearing prices are calculated when determining the price of electricity. Estimating hourly market prices and quantities in daily energy markets is one of the most fundamental tasks and decisions in any decision making. The approach to forecasting market conditions is to use past prices and quantities to estimate future prices and quantities to be placed on the market.(Gao et al, 2000)

Estimating market clearing prices plays a key role in keeping the costs of investors and sector representatives active in the market as low as possible and maximizing profit rates. Therfore, prediction of market clearing price are very important for price changes. In addition to, weather condition and stock index also affect the market price of electricity. It is not easy to predict market prices and to be suitable for reality, and neural networks are often used to reach this conclusion.(JJ Guo et al, 2004).

1.2. Motivation and Purpose of this Thesis

Rapid development is observed in the electricity and energy market in Turkey. The competition in the electricity and energy markets and the determination of the electricity prices of the companies are of great importance. In this process, accurate estimation of the market clearance price plays an important role in creating the supply-demand balance.

Machine learning is widely used to predict the future based on an analysis of the most common trends of the past. Numerous studies have been done in the field of machine learning and many articles have been written, and among them Neural Networks are more than other machine learning methods(Makridakis et al., 2018).

The subject of this project is to estimate the market clearing price of electricity using machine learning and deep learning methods. The following works will be carried out within the scope of the project:

- Creating different models with variables affecting market clearing price.
- Separate each data set into training set and test set when creating models.
- Using MLP, CNN, RNN and LSTM methods as machine learning and deep learning methods for machine learning and modeling.
- Calculation of performance MAPE values of models and performance analysis of the methods according to the results.

The aim of this thesis is to estimate the market clearing price of electricity by using machine learning and deep learning methods. The machine learning methods that will be employed are Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM).

1.3. Literature Review

Several academic studies have been done in literature which forecast market clearing price of electricity with machine learning methods. In(Ni et. al., 2001) a new model was developed to estimate the market clearing price by using the classification method and the automatic regression model, and it was observed that this method had better performance than the RBF according to the estimation results obtained. In(Guo et. al., 2003) when Gaussian functions were created by using Gaussian radial basic function (GRBF) networks, an education model was applied in contrast to standard deviations and it was found to have a significant effect on market clearing price forecast performance.

In(Foruzan et. al., 2015) artificial neural networks (ANNs) and support vector machines (SVM) were used for electricity price prediction. In the methods used by the authors, SVM has a higher error rate.

In(Abedinia et. al., 2015) Wavelet Transform (WT), AutoRegressive Integrated Moving Average (ARIMA) and Radial Basic Function Neural Networks (RBFN) and mixed method to estimate the day ahead price of the electricity market and the results were shown to be acceptable.

In(Saini et. al., 2016) in order to estimate the electricity price, a mixed model was obtained by using linear regression and Support Vector Machine (SVM) together and this mixed model gave better results than the others.

In(Chinnathambi et. al., 2016) Automatic Regressive Integrated Moving Average (ARIMA), Random Forest (RF), Generalized Linear Model (GLM) and Support Vector Machines (SVM) methods were used. When the mean Absolute Percentage Error (MAPE) values were measured, it was concluded that MAPE values were better for ARIMA-GLM method.

In(Kumar et. al., 2016) in this study, Artificial Neural Network (ANN) and Regression model are used by the authors to predict Market Clearing Prices in Indian Electricity Markets.

In this study, Artificial Neural Network (ANN) and Regression model are used by the authors to predict Market Clearing Prices in Indian Electricity Markets. ANN and Regression methods were applied in the models and it was found that Regression model gave more consistent and better results than ANN model by evaluating Mean Absolute Percent Error (MAPE) values.

In(Chinnathambi et. al., 2018) hourly spot prices forecast for electricity markets Automatic Decline Integrated Moving Average (ARIMA) and one of the other methods were selected and variables such as price, load and temperature were used together. According to the results of the Mean Absolute Percentage Error (MAPE), it was stated that ARIMA-SVM method had better performance for short periods, whereas ARIMA-GLM merhod had better performance for longer periods.

In(Yu et. al., 2018) this study shows that the automatic regressing moving average (ARMA) model can be used in electricity price estimation and better results can be obtained by developing the ARMA model for the day ahead forecast.

In(Kuo et. al., 2018) Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) by authors to accurately estimate the price of electricity. In this study using deep learning neural networks, it has been proved that these methods and models can be applied while making electricity price estimation. In this study, Mean Absolute Error (MAE) and Root Mean Frame Error (RMSE) evaluation methods were used and it was seen that the model used together with CNN and LSTM gave lower error values.

Summarizes some of the important studies in the literature related to the market clearing of the estimated electricity price ordered by a chronological order in Table 1.1.

Table 1.1. Summary of the recent studies about prediction of market clearing price

Study	Methods	Writers
A Comparative Study of Different Machine Learning Methods for Electricity Prices Forecasting	ANN, SVM	Foruzan et. al., 2015
Day ahead Price Forecasting of Electricity Markets by a New Hybrid Forecast Method	WT, ARIMA, RBFN	Abedinia et. al., 2015
Electricity Price Forecasting by Linear Regression and SVM	LR, SVM	Saini et. al., 2016
Market clearing price prediction using ANN in indian electricity markets	ANN and Regression model	Kumar et. al., 2016
Investigation of forecasting methods for the hourly spot price of the day ahead electric power markets	ARIMA, RF, GLM, SVM, ARIMA-GLM	Chinnathambi et. al., 2016
Day Ahead Electricity Market Clearing Price Forecasting	ARMA	Yu et. al., 2018
A Multi-Stage Price Forecasting Model for Day-Ahead Electricity Markets	ARIMA, ARIMA-SVM, ARIMA-GLM	Chinnathambi et. al., 2018
An electricity price forecasting model by hybrid structured deep neural Networks	CNN, LSTM	Kuo et. al., 2018

ANN, Artificial Neural Network; **ARIMA,** Auto-Regressive Integrated Moving Average; **ARIMA-GLM,** Auto-Regressive Integrated Moving Average-Generalized Linear Model; **ARIMA-SVM,** Auto-Regressive Integrated Moving Average-Support Vector Machine; **ARMA,** Auto-Regressive Moving Average; **CNN,** Convolutional Neural Network; **GLM,** Generalized Linear Model;

LR, Linear Regression; **LSTM,** Long-Short Term Memory; **MLP,** Multilayer Perceptron; **MLP,** Multilayer Perceptron; **RBFN,** Radial Basis Function Network; **RF,** Random Forest; **SVM,** Support Vector Machine; **WT,** Wavelet Transform;

In the period from 2001 to the present day, it is seen that the studies about the daily market clearing price prediction are generally used machine learning and deep learning methods. It has been observed that these studies have been using traditional models in previous years, especially with the development of modern era since 2015, it is seen that more machine learning and deep learning methods are used in maximum levels and this progress is revised and error rates are approached to more minimized results.

1.4. Contributions of the Thesis

When the studies related to the prediction of the electricity market clearing price in the literature are examined, it is seen that the prediction models developed are generally machine learning based. Although many different machine learning methods are used in the development of prediction models, it has been observed that deep learning methods are less used besides machine learning based prediction models and studies in this field are inadequate. Within the scope of the project, this gap in the literature will be filled by using machine learning and deep learning methods and with the models created using machine learning and deep learning methods;

1. low error rate estimation results will be achieved.
2. In this way, performances of machine learning and deep learning based methods will be measured and more accurate predictions will be produced.
3. New forecasting models will be produced and therefore more accurate market clearing price forecasts will be made in this sector.

1.5. Overview of the Dataset

In this thesis, market clearing price data sets will be used for the prediction attempts the period of 01.01.2016 to 01.01.2018. Datasets have been provided from (https://seffaflik.epias.com.tr) website.

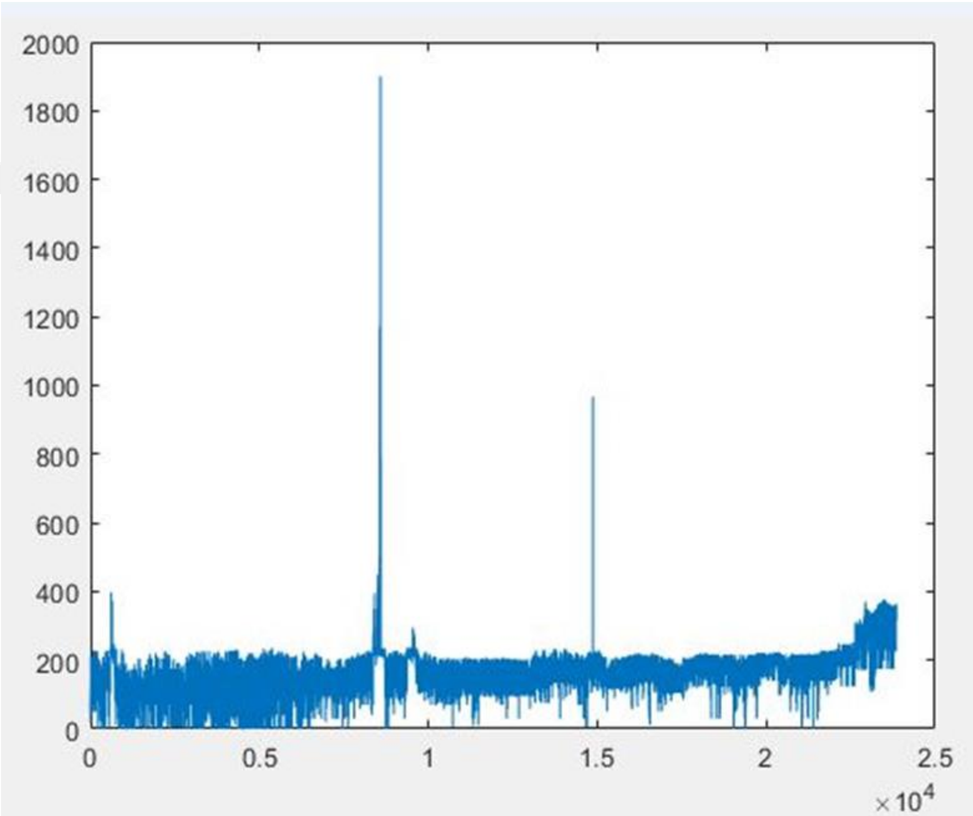

Figure 1.1. Hourly PTF dataset

2. OVERVIEW OF METHODS

The machine learning methods to be used will be Multilayer Sensor (MLP), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM).

2.1. Multi-Layer Perceptron

A multi-layer perceptron(MLP) is a forward-looking artificial neural network. In an MLP, it basically consists of three node layers. These are considered as input layer, hidden layer and output layer.

Artificial neural networks are found mainly in layers. The layers in a layered network contain neurons, and the information in these layers passes through these three complementary units. All elements receive input signals and transmit output signals to elements in subsequent layers. Thus, the flow of information in the functioning neurons can be observed in the Multilayer Perceptron. (MLP) (Figure 2.1).

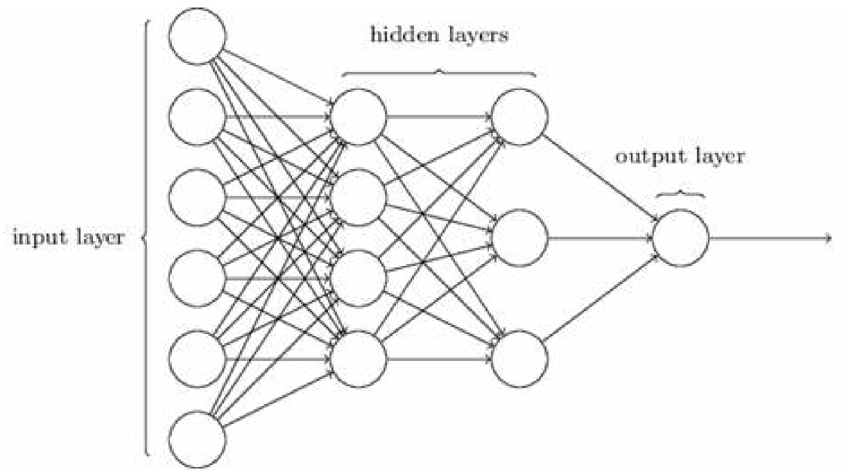

Figure 2.1. A Standard MLP Network

Although MLP networks typically contain three element layers, which are a hidden layer, there may be an increase in the number of layers relative to usage. The purpose of the input layer is to take the external information and transfer it to the next layer. The hidden layer receives the weighted sum of the signals from the input. (2.1)

$$SUM = \sum_{i=1}^{n} XiWi \qquad (2.1.)$$

Enters the found sum to the activation function. The sigmoid (2.2) and hyperbolic tangent (2.3) functions are frequently used as activation functions.

$$f(x) = \frac{1}{1+e^{-x}} \quad (2.2.)$$

$$f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \quad (2.3.)$$

The multilayer neural network is trained using input and output values. The neural network generates an output value for each input value. The accuracy of the generated output value is measured by an error E defined as the difference between the current op and the desired output tp (2.4).

$$E = \frac{1}{2}\sum_{j}(t_{pj} - o_{pj})^{2} \quad (2.4.)$$

In order to minimize the total error, the values of the weights are changed and the calculated E error is propagated from the output towards the input layer. Appropriate adjustments are made by replacing the weights in the neural network with a ratio d of the total error E.

2.2. Long Short Term Memory

Long Short Term Memory (LSTM) was discovered in 1997 by S. Hochreiter and J. Schmidhuber. With repetitive back propagation of the information, it costs a lot of time to learn to store the information over long periods of time, and because of the ever-decreasing error backflow. Long short term memory (LSTM) is the solution to this problem, and it has been found to be effective in solving this problem. LSTM applies constant error flow by using the fixed error carousel in its special units and provides learning in this way.(Hochreiter and Schmidhuber 1997)

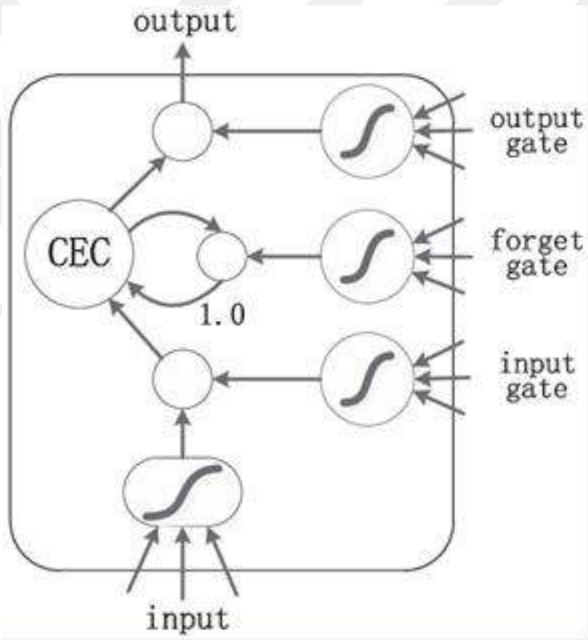

Figure 2.2. Provides an illustration of a single-cell LSTM memory block.

The LSTM method consists of interconnected subnets and memory blocks. These blocks include memory cells with variable number of write, read and reset functions in the cells, and three multiplicity entry doors, exit doors, and forget doors. The structure of the LSTM network is the same as with RNN, but memory blocks must be used instead of nonlinear units in the hidden layer. LSTM blocks can be used with other units in some cases. Further, as with RNN method, the hidden layer may be added to the derivatizable output layer as desired.

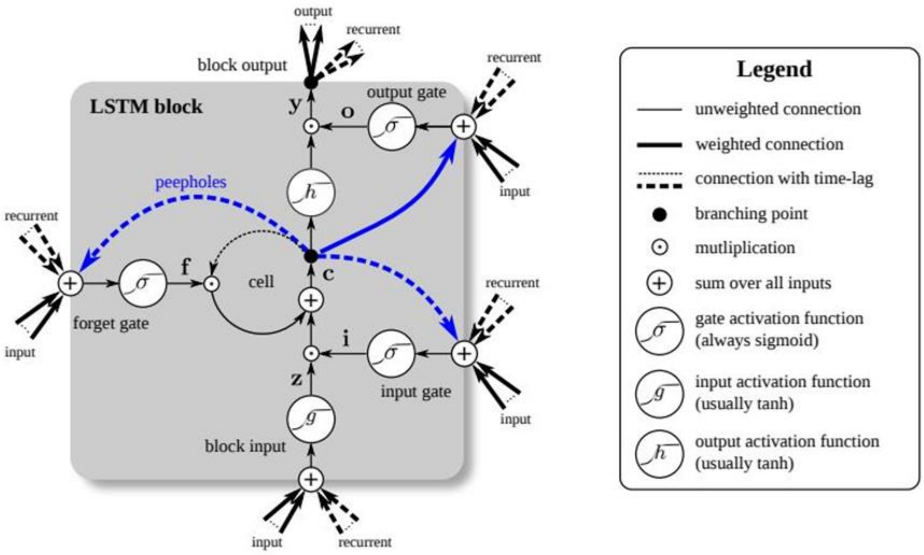

Figure 2.3. Design of the memory unit of LSTM

The LSTM network, which acts as a hidden layer memory unit, is a type of RNN and allows the expression and understanding of the correlation between time series over short and long periods of time. The structure of a standard memory unit is shown in Figure 2.3. a memory cell is located in the center of the unit. It also contains input data and output data. Output data represents the estimate result. The memory unit contains three doors, as shown in the entry door, entrance door and exit door.(Zhao et. al., 2017)

2.3. Recurrent Neural Network

Recurrent neural networks are used in conjunction with feedback links, and RNNs are capable of expressing some computational structures. In the training of RNNs, short-term dependencies are more likely to be calculated, and long-term dependencies tend to be neglected.(Giles et. al., 2001)

Although conventional neural networks have full connections between adjacent layers, there is no connection between nodes within the same layer. Since there are often some interactions between nodes in the temporal network, such networks may face temporal problems. The sections in the RNN contain feedback from the previous state to the current state..(Zhao et. al., 2017)

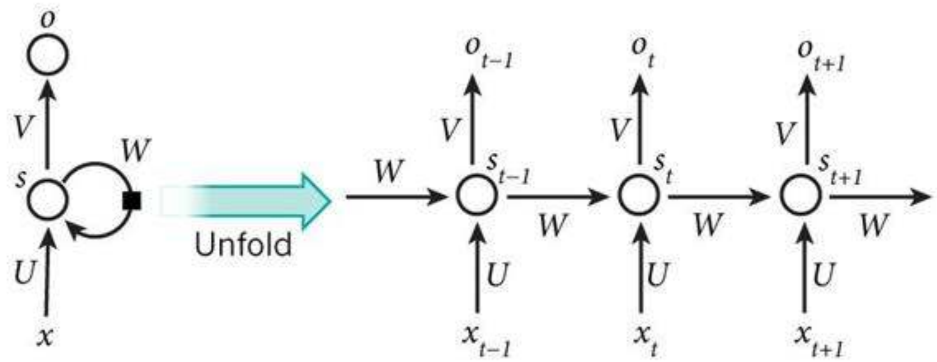

Figure 2.4. Basic structure of RNN

Figure 2.4 illustrates a basic RNN architecture. RNN shows a folded network in the time domain for two time stages. This structure does not have a fixed number of input vectors, and unlike conventional network structures, the input vectors are introduced into the network. This architecture can benefit from the input information it uses. Furthermore, due to this structure, it can be seen that the output is not only connected to the current input but also to the output of the previous hidden layer.(Zhao et. al., 2017)

2.4. Convolutional Neural Network

Convoluted Neural Network (CNN) is a deep learning class and has proven to be very efficient when used in pattern recognition. It has also been used successfully in speech recognition and image classification. It performed well in the ImageNet competition held in 2012 in the field of image classification(Botalb et. al., 2018). Also, convolutional network was presented as a method of estimating time series using a Relu activation function and applying multiple convolution filters, and this convolutional network with extended convolutions enabled rapid processing of thedata (Borovykh et. al., 2017). One-dimensional convolutional neural networks can be used to predict time series and to learn time series dependencies.The one-dimensional convolution and pooling layer is presented in Figure 2.5. Lines of the same color indicate the same share weight. After convolution, inputs x1, x2, x3, ..., x6 are converted to feature maps c1, c2, c3, c4. The next step in Figure 2.5 is pooling, where the property map of the convolution layer is the size of the sample shadows.For instance,in 4 dimensions exist in the feature map in Figure 2.5, after the pooling process the number of dimensions is reduced to 2. The process of pooling is an important step to demonstrate the convolution network characteristics.(Kuo et. al., 2018)

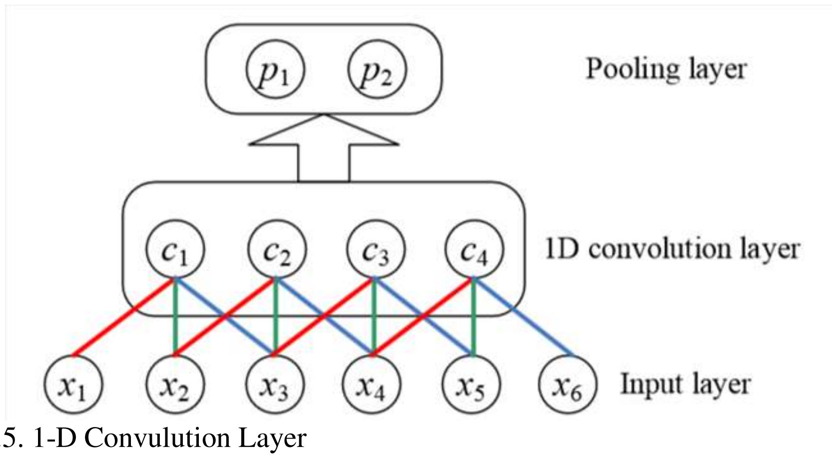

Figure 2.5. 1-D Convulution Layer

3. DEVELOPMENT OF PREDICTION MODELS

3.1. Time Series Analysis

Machine learning and deep learning methods used in this thesis, time series analysis was used to forecast future values. The values in the data set consist of time-acquired data and time delays are effectively used for methods. Thus, time series forecasting is used to estimate future data.

3.2. Environment

In this thesis, MLP, LSTM, RNN forecast models are developed by using MATLAB R2018a and CNN forecast models are developed by using Keras libraries. In addition, Neural Network Toolbox produced by MATLAB was used for the neural network when forecast models and methods were created.

3.3. Time Lag and Autocorrelation function

Time lag in time series forecast is a parameter used in time series analysis. It is usually obtained by shifting the data as necessary. In this thesis, the autocorrelation values of the data sets were calculated using the delay values. Autocorrelation in data sets is an important element in time series. Autocorrelation can be expressed as the correlation between any time shift and itself. In this thesis, feedback delays, one of the optimizations applied to the neural network, are established by using autocorrelation values.

Autocorrelation graphs for the dataset used in this thesis are shown in Figures 3.1.

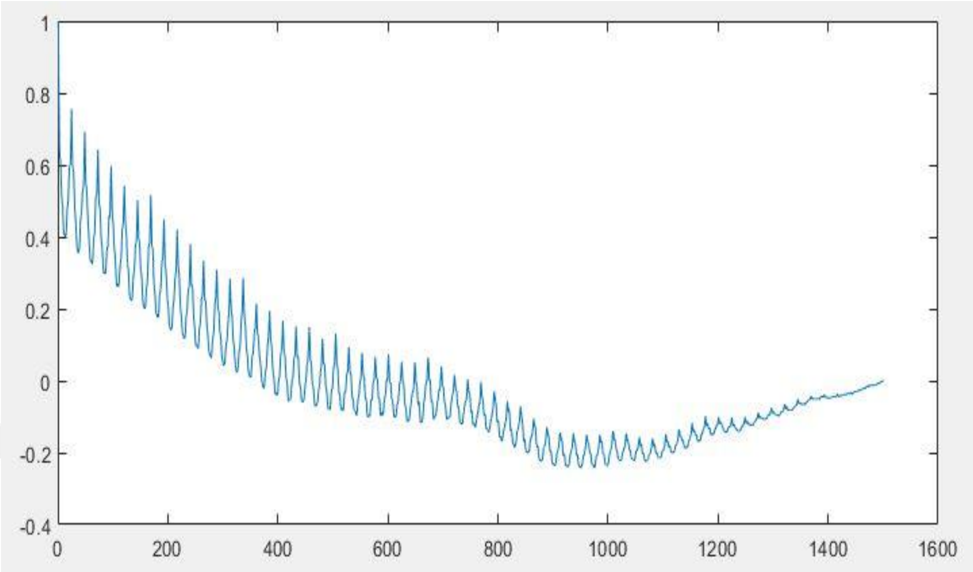

Figure 3.6. Autocorrelations for dataset

3.4. Optimization Parameters

This software contains some basic parameters of artificial neural networks produced using machine learning and deep learning methods. These parameters significantly affect the results of artificial neural networks. In addition to, the hiden layer size, feedback delays, epoch number and hidden units described below have been optimized by the user and the software, thereby increasing the efficiency of the artificial neural networks.

3.4.1. Feedback Delays

Feedback delays, which are used as one of the main parameters in time series forecast, are obtained by calculating the delayed state of the dataset. In this software, feedback delay values can be optimized by specifying an index number with a desired autocorrelation value, entering the number of indices with the highest autocorrelation of the user, or using indices whose autocorrelations are higher than a certain threshold. In addition to, autocorrelation graphs can be obtained upon request from the user.

3.4.2. Hidden Layer Size

Different hidden layer sizes are used for the artificial neural network prediction model in this software. The user-specified hidden layer size includes one, two, or three layer sizes. When the user selects a layered hidden layer, the program calculates the optimal value by experimenting one by one with a specific value or any other value. The last 500 and 1500 value ranges of the data set used in the software were divided into training data set and models were created. In addition, after the hidden layer size is determined by one, two or three layer sizes, the values up to that value are calculated by the software and the highest performance layer sizes are calculated in the results section of the program and shown to the user. In the software, this hidden layer is optimized and sub-models are created which give the lowest error rate.

3.4.3. Number of Epoch

The performance of models created using artificial neural networks is tested after training and weights are updated using back propagation. In order to calculate the most appropriate weight values in the obtained model, it is repeated in each training step and these steps which are called as epoch are determined according to the performance of the model. When the performance of the model reached the highest levels, approximately the number of epochs was determined. In this study, models were created by taking into account the number of epochs while applying LSTM and CNN deep learning methods.

3.4.4. Hidden Units

The hidden unit of an LSTM layer is an important parameter in measuring the dependencies between the data set in time series when learning from deep learning methods with long short term memory. The number of hidden units corresponds to the amount of information recalled between time steps and may include information of the data from previous time steps independent of the data set. In this thesis, different models have been formed by applying different hidden unit numbers while using LSTM method.

3.5. Model Configuration

In this thesis, MLP, RNN, LSTM and CNN methods, which are machine learning and deep learning methods, are applied by the software developed in MATLAB environment. In the software, the data set is loaded into the system firstly and one of the specified machine and deep learning methods is selected by the user. The method chosen is of great importance for the structure of the artificial neural network. The required parameters for MLP, RNN, LSTM and CNN methods are displayed in the artificial neural network to be created. Necessary index dataset information is entered by the user to teach the artificial neural network. The index values of the range to be taught of the data set loaded into the learning part of the software's prediction section are entered in the 1st and 2nd text boxes. The autocorrelation graph of the data to be used for training can be drawn graphically by the program.

After loading the dataset on the artificial neural network, one of the machine and deep learning methods, MLP, RNN, LSTM and CNN methods are selected. After the determined machine and deep learning method, the required value ranges are entered in the learning index section according to the prediction model. Any interval specified in the data set can be entered according to the prediction model to be used.

If 5000 and 10000 values are entered as an example, it means that the data in this range will be used for learning. The remaining data after the training data determined from the data set are the data to be estimated. One of the delay optimizations determined according to artificial neural network models is determined. Delay values are entered according to the forecast models created. For example, 7.3.12 delay values or 2.26.52.61.143 delay values can be used. After determining the required optimization values, the program is run. After learning, the values after the learning data in the dataset are estimated. After the data entered into the system to learn during the prediction process, new values that are not present after the program data set are estimated. The estimates obtained and the actual values in the data set are printed in the table on the results page and the graphics of them are drawn. As a measure of the relationship between these values, mape (average absolute percent error) is calculated and this value is printed on the screen.

3.6. Functions used in Prediction Models

This software has benefited from some of the functions offered by MATLAB R2018a and Keras libraries. These functions have a significant impact on the creation of MLP, LSTM, RNN and CNN prediction models while coding in the software. Therefore, it will be explained in which tasks the important functions are used.

Functions used to load, read and graph the data set:

uigetfile: Allows the user to specify the file path to load the dataset.

csvread: Provides the reading of the data set with the csv extension determined by the user.

plot: Creates a 2 dimensional line chart of data in Y against corresponding values in X.

Main functions used for MLP and RNN neural network models:

narnet: NAR (nonlinear autoregressive) function that creates neural network.

layrecnet: The main method used to create a model of recurrent neural networks**.**

preparets: prepares time series data using the narnet network.

train: Used for training the created network model.

Main functions used for LSTM neural network models:

sequenceInputLayer: A sequence input layer inputs sequence data to a network.

lstmLayer: An LSTM layer learns long-term dependencies between time steps in time series and sequence data.

fullyConnectedLayer: A fully connected layer multiplies the input by a weight matrix and then adds a bias vector.

trainingOptions: Options for training deep learning neural network

trainNetwork: Train neural network for deep learning

predictAndUpdateState: Predict responses using a trained recurrent neural network and update the network state.

Main functions used for CNN neural network models:

Sequential: Groups an ordered and linear layer stack into a model.

Add: Adds a layer to the created model.

Conv1D: 1D convolution layer creates a convolution kernel that passes over a single spatial dimension to produce a tensor of outputs..

MaxPooling1D: Reduces the size from the convolutional layer over the window according to the pool size.

Fit: Used to train the convolutional network Model.

Predict: The function used to predict the convolutional network model.

3.7. Performance Metric

The performance of the prediction models was evaluated by calculating the values of Mean Absolute Percentage Error (MAPE), which is the metric popularly used for the forecasting applications.

The formula of MAPE is given by

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|A_t - F_t|}{F_t}$$

where n is the number of the forecast, A_t is the actual value, and F_t is the forecast value (Benzer et al., 2015).

3.8. Screenshots

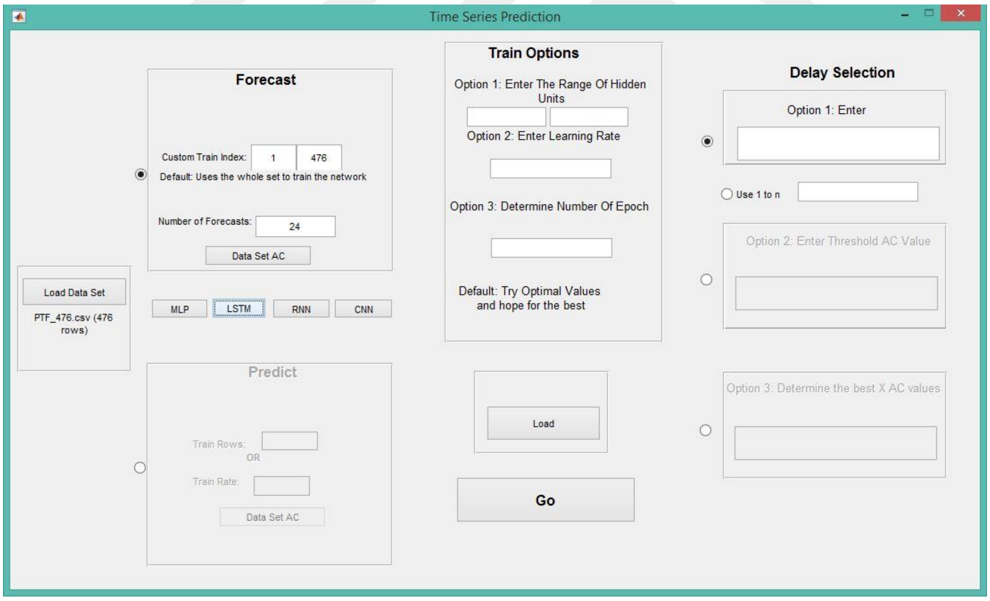

Figure 3.1. Data set loaded and one of the machine and deep learning methods was selected

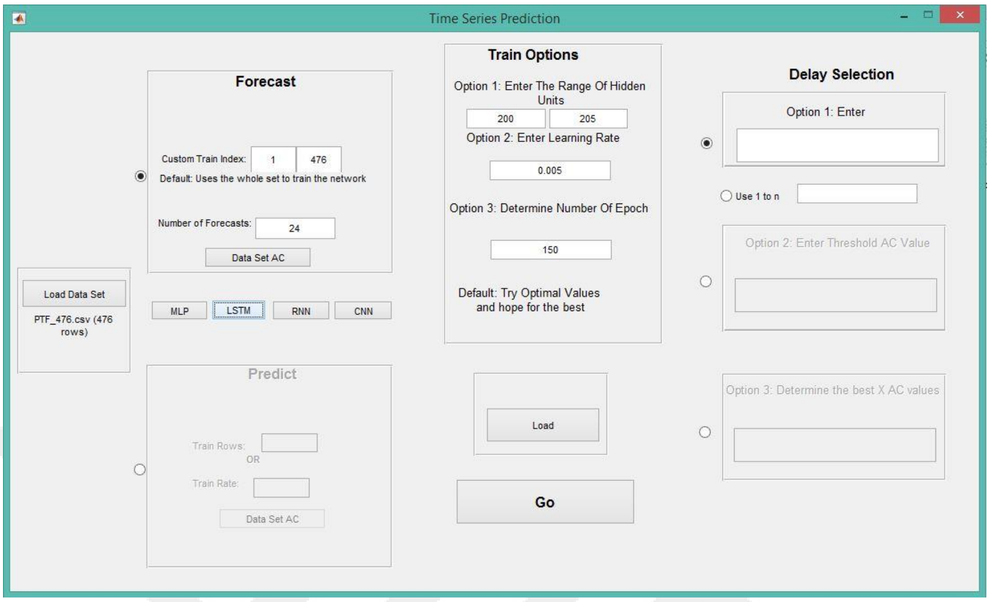

Figure 3.2. Necessary optimization values were entered according to the selected machine and deep learning method

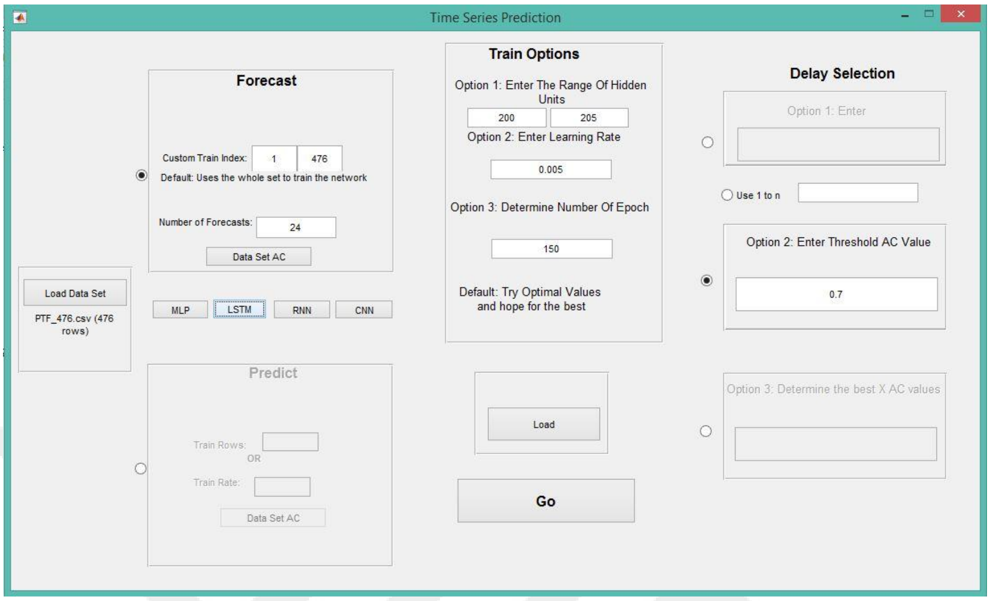

Figure 3.3. One of the delay optimizations determined according to artificial neural network models is selected

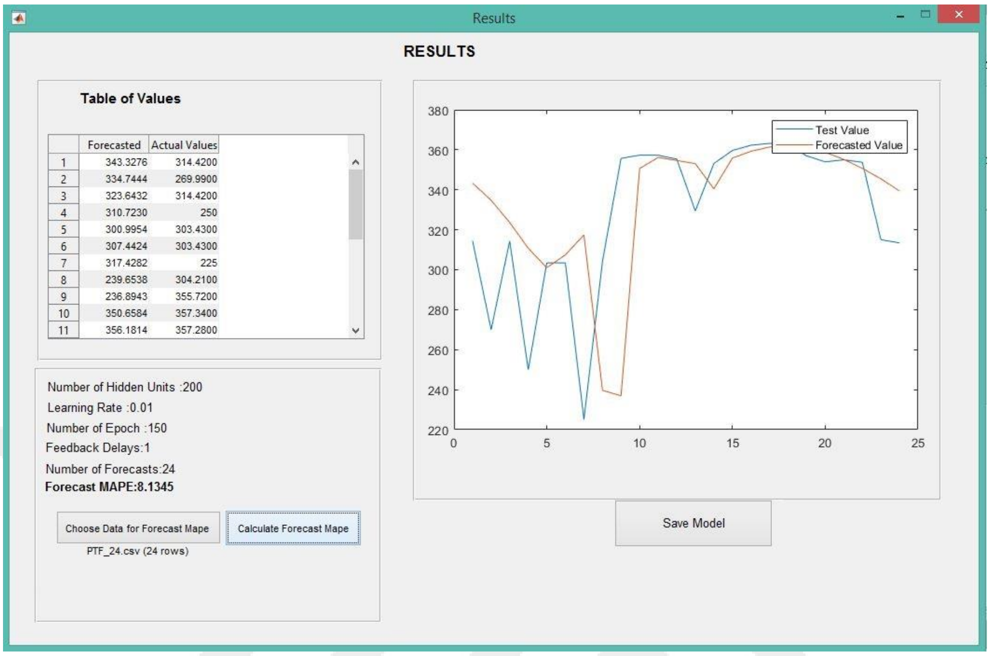

Figure 3.4. The estimates obtained and the actual values in the dataset are printed in the table and the mape value is calculated

4. RESULTS AND DISCUSSIONS

In this thesis, MLP, LSTM, RNN and CNN are used to estimate the market clearing price. A combination of 80% for training and 20% for the test was used to generate prediction models. Prediction models were developed by increasing the last 500 to 1500 part of the dataset by 100. Prediction models include 24 step estimates and 1, 2 and 3 hidden layer sizes are used. In the delay selection, the highest autocorrelation indexes 5, 7 and 9, autocorrelation indexes greater than 0.7, 0.8 and 0.9 and indexes 1 to 5, 15 and 25 were used.

Tables 5.1 to 5.78 show MLP results, tables 5.79 to 5.156 show LSTM results, tables 5.79 to 5.156 show CNN results, tables 5.79 to 5.156 show RNN results.

Table 4.1. MAPE values (476, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	6	1,2,25,49,73	14.57
24	1	Best 7 A.C.	5	1,2,25,49,73,97,169	9.52
24	1	Best 10 A.C.	10	1,2,24,25,26,49,73,97,121,169	8.98
24	1	A.C. >0.7	10	1	13.13
24	1	A.C. >0.8	10	1	12.09
24	1	A.C. >0.9	3	1	12.31
24	1	1 to n	6	1 to 5	10.36
24	1	1 to n	3	1 to 15	13.99
24	1	1 to n	8	1 to 25	7.8

Table 4.2. MAPE values (476, 2 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	MAPE
24	2	Best 5 A.C.	9,8	1,2,25,49,73	8.83
24	2	Best 7 A.C.	7,8	1,2,25,49,73,97,169	7.14
24	2	Best 10 A.C.	7,4	1,2,24,25,26,49,73,97,121,169	8.99
24	2	A.C. >0.7	8,9	1	14.11
24	2	A.C. >0.8	9,7	1	15.33
24	2	A.C. >0.9	9,7	1	14.9
24	2	1 to n	9,5	1 to 5	12.48
24	2	1 to n	9,10	1 to 15	12.03
24	2	1 to n	8,8	1 to 25	10.24

Table 4.3. MAPE values (476, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	MAPE
24	3	Best 5 A.C.	6,4,10	1,2,25,49,73	12.87
24	3	Best 7 A.C.	8,5,10	1,2,25,49,73,97,169	9.08
24	3	Best 10 A.C.	10,10,8	1,2,24,25,26,49,73,97,121,169	10.18
24	3	A.C. >0.7	8,6,5	1	9.8
24	3	A.C. >0.8	10,7,7	1	14.53
24	3	A.C. >0.9	8,2,10	1	11.74
24	3	1 to n	10,10,9	1 to 5	15.57
24	3	1 to n	8,10,8	1 to 15	17.76
24	3	1 to n	9,6,4	1 to 25	10.22

Table 4.4. MAPE values (576, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	1	1,2,25,49,73	12.56
24	1	Best 7 A.C.	8	1,2,25,49,73,97,169	9.97
24	1	Best 10 A.C.	5	1,2,25,49,73,97,121,145,169	14.98
24	1	A.C. >0.7	10	1	13.75
24	1	A.C. >0.8	10	1	12.46
24	1	A.C. >0.9	8	1	17.11
24	1	1 to n	6	1 to 5	13.02
24	1	1 to n	6	1 to 15	16.36
24	1	1 to n	10	1 to 25	7.78

Table 4.5. MAPE values (576, 2 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	4,7	1,2,25,49,73	9.01
24	2	Best 7 A.C.	9,8	1,2,25,49,73,97,169	8.69
24	2	Best 10 A.C.	10,8	1,2,25,49,73,97,121,145,169	7.6
24	2	A.C. >0.7	9,2	1	15.69
24	2	A.C. >0.8	4,7	1	15.86
24	2	A.C. >0.9	10,9	1	15.44
24	2	1 to n	8,4	1 to 5	9.48
24	2	1 to n	8,2	1 to 15	14.06
24	2	1 to n	9,9	1 to 25	8.03

Table 4.6. MAPE values (576, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	3	Best 5 A.C.	7,4,8	1,2,25,49,73	12.11
24	3	Best 7 A.C.	10,3,8	1,2,25,49,73,97,169	10.25
24	3	Best 10 A.C.	9,7,5	1,2,25,49,73,97,121,145,169	12.64
24	3	A.C. >0.7	10,1,6	1	11.26
24	3	A.C. >0.8	9,10,9	1	10.4
24	3	A.C. >0.9	9,8,10	1	10.29
24	3	1 to n	9,9,6	1 to 5	15.77
24	3	1 to n	10,6,5	1 to 15	17.46
24	3	1 to n	9,10,1	1 to 25	7.71

Table 4.7. MAPE values (676, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	9	1,2,25,49,73	12.68
24	1	Best 7 A.C.	1	1,2,25,49,73,97,169	12.34
24	1	Best 10 A.C.	8	1,2,25,49,73,97,121,145,169	11.22
24	1	A.C. >0.7	4	1	13.13
24	1	A.C. >0.8	4	1	11.39
24	1	A.C. >0.9	2	1	12.98
24	1	1 to n	7	1 to 5	13.47
24	1	1 to n	10	1 to 15	14.71
24	1	1 to n	8	1 to 25	13.21

Table 4.8. MAPE values (676, 2 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	7,10	1,2,25,49,73	14.05
24	2	Best 7 A.C.	6,8	1,2,25,49,73,97,169	9.72
24	2	Best 10 A.C.	8,10	1,2,24,25,26,49,73,97,169,217	10.84
24	2	A.C. >0.7	4,8	1	16.54
24	2	A.C. >0.8	10,10	1	14.54
24	2	A.C. >0.9	4,6	1	15.31
24	2	1 to n	2,9	1 to 5	10.3
24	2	1 to n	7,8	1 to 15	10.8
24	2	1 to n	9,8	1 to 25	13.74

Table 4.9. MAPE values (676, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	3	Best 5 A.C.	5,7,1	1,2,25,49,73	13.02
24	3	Best 7 A.C.	6,8,10	1,2,25,49,73,97,169	12.63
24	3	Best 10 A.C.	9,4,7	1,2,24,25,26,49,73,97,169,217	12.53
24	3	A.C. >0.7	10,8,10	1	17.35
24	3	A.C. >0.8	3,1,7	1	13.87
24	3	A.C. >0.9	5,10,6	1	17.62
24	3	1 to n	10,9,6	1 to 5	14.33
24	3	1 to n	6,10,1	1 to 15	10.88
24	3	1 to n	10,9,6	1 to 25	12.54

Table 4.10. MAPE values (776, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	7	1,2,25,49,73	14.68
24	1	Best 7 A.C.	8	1,2,24,25,49,73,97	17.81
24	1	Best 10 A.C.	2	1,2,24,25,26,49,72,73,97,169	19.54
24	1	A.C. >0.7	8	1	13.37
24	1	A.C. >0.8	6	1	15.14
24	1	A.C. >0.9	5	1	17
24	1	1 to n	10	1 to 5	22
24	1	1 to n	9	1 to 15	7.21
24	1	1 to n	7	1 to 25	16.87

Table 4.11. MAPE values (776, 2 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	7,10	1,2,25,49,73	18.17
24	2	Best 7 A.C.	4,5	1,2,24,25,49,73,97	23.06
24	2	Best 10 A.C.	10,3	1,2,24,25,26,49,72,73,97,169	17.04
24	2	A.C. >0.7	5,4	1	15.81
24	2	A.C. >0.8	5,3	1	12.87
24	2	A.C. >0.9	6,3	1	14.14
24	2	1 to n	9,5	1 to 5	12.17
24	2	1 to n	7,2	1 to 15	9.44
24	2	1 to n	6,6	1 to 25	17.07

Table 4.12. MAPE values (776, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	3	Best 5 A.C.	10,10,4	1,2,25,49,73	12.37
24	3	Best 7 A.C.	10,6,8	1,2,24,25,49,73,97	18.95
24	3	Best 10 A.C.	9,6,2	1,2,24,25,26,49,,72,73,97,169	16.49
24	3	A.C. >0.7	9,10,8	1	11.84
24	3	A.C. >0.8	10,7,10	1	15.17
24	3	A.C. >0.9	9,7,9	1	15.83
24	3	1 to n	9,9,9	1 to 5	11.52
24	3	1 to n	9,7,7	1 to 15	7.22
24	3	1 to n	9,6,4	1 to 25	18.11

Table 4.13. MAPE values (876, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	6	1,2,25,49,73	11.10
24	1	Best 7 A.C.	9	1,2,25,49,73,97,169	11.65
24	1	Best 10 A.C.	7	1,2,24,25,26,49,73,97,121,169	16.86
24	1	A.C. >0.7	7	1	14.71
24	1	A.C. >0.8	5	1	16.65
24	1	A.C. >0.9	6	1	10.37
24	1	1 to n	10	1 to 5	18.14
24	1	1 to n	10	1 to 15	7.7
24	1	1 to n	8	1 to 25	15.79

Table 4.14. MAPE values (876, 2 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	10,9	1,2,25,49,73	11.7
24	2	Best 7 A.C.	5,7	1,2,25,49,73,97,169	11.56
24	2	Best 10 A.C.	8,4	1,2,24,25,26,49,73,97,121,169	16.6
24	2	A.C. >0.7	6,7	1	15.1
24	2	A.C. >0.8	5,5	1	10.31
24	2	A.C. >0.9	8,10	1	16.90
24	2	1 to n	7,6	1 to 5	10.33
24	2	1 to n	8,7	1 to 15	9.07
24	2	1 to n	10,7	1 to 25	16.95

Table 4.15. MAPE values (876, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	3	Best 5 A.C.	8,7,8	1,2,25,49,73	11.35
24	3	Best 7 A.C.	8,6,4	1,2,25,49,73,97,169	14.5
24	3	Best 10 A.C.	9,7,5	1,2,24,25,26,49,73,97,121,169	15.35
24	3	A.C. >0.7	5,10,9	1	14.11
24	3	A.C. >0.8	9,9,8	1	13.25
24	3	A.C. >0.9	7,5,10	1	12.49
24	3	1 to n	9,5,8	1 to 5	12.18
24	3	1 to n	8,7,6	1 to 15	13.46
24	3	1 to n	9,9,10	1 to 25	16.63

Table 4.16. MAPE values (976, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	5	1,2,25,49,73	10.49
24	1	Best 7 A.C.	8	1,2,25,49,73,97,169	11.35
24	1	Best 10 A.C.	7	1,2,24,25,26,49,50,73,97,169	10.83
24	1	A.C. >0.7	8	1	16.38
24	1	A.C. >0.8	2	1	14.47
24	1	A.C. >0.9	5	1	16.43
24	1	1 to n	10	1 to 5	15.32
24	1	1 to n	10	1 to 15	9.91
24	1	1 to n	8	1 to 25	13.62

Table 4.17. MAPE values (976, 2 layers, MLP)

Number of Forecast	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	1,2	1,2,25,49,73	13.38
24	2	Best 7 A.C.	9,9	1,2,25,49,73,97,169	11.95
24	2	Best 10 A.C.	9,4	1,2,24,25,26,49,50,73,97,169	11.31
24	2	A.C. >0.7	9,8	1	16.1
24	2	A.C. >0.8	7,8	1	13.23
24	2	A.C. >0.9	5,6	1	15.7
24	2	1 to n	8,8	1 to 5	18.9
24	2	1 to n	10,4	1 to 15	8.75
24	2	1 to n	10,9	1 to 25	11.12

Table 4.18. MAPE values (976, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	3	Best 5 A.C.	8,5,1	1,2,25,49,73	13.14
24	3	Best 7 A.C.	10,4,5	1,2,25,49,73,97,169	12.13
24	3	Best 10 A.C.	9,8,9	1,2,24,25,26,49,50,73,97,169	11.96
24	3	A.C. >0.7	8,9,9	1	15.28
24	3	A.C. >0.8	9,4,9	1	10.44
24	3	A.C. >0.9	9,7,9	1	14.36
24	3	1 to n	8,10,7	1 to 5	10.29
24	3	1 to n	3,8,9	1 to 15	8.46
24	3	1 to n	4,10,4	1 to 25	15.05

Table 4.19. MAPE values (1076, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	5	1,2,25,49,73	13.10
24	1	Best 7 A.C.	7	1,2,24,25,49,73,97	12.52
24	1	Best 10 A.C.	4	1,2,24,25,26,48,49,50,73,97	16.29
24	1	A.C. >0.7	10	1	18.94
24	1	A.C. >0.8	8	1	18.75
24	1	A.C. >0.9	7	1	18.12
24	1	1 to n	7	1 to 5	13.02
24	1	1 to n	1	1 to 15	10.53
24	1	1 to n	9	1 to 25	15.23

Table 4.20. MAPE values (1076, 2 layers, MLP)

Number of Forecast	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	8,8	1,2,25,49,73	12.72
24	2	Best 7 A.C.	6,2	1,2,24,25,49,73,97	15.44
24	2	Best 10 A.C.	5,5	1,2,24,25,26,48,49,50,73,97	16.82
24	2	A.C. >0.7	7,5	1	15.54
24	2	A.C. >0.8	7,8	1	14.36
24	2	A.C. >0.9	8,5	1	17.16
24	2	1 to n	8,2	1 to 5	16.58
24	2	1 to n	9,6	1 to 15	8.72
24	2	1 to n	9,3	1 to 25	13.76

Table 4.21. MAPE values (1076, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	3	Best 5 A.C.	9,10,9	1,2,25,49,73	14.64
24	3	Best 7 A.C.	10,2,5	1,2,24,25,49,73,97	14.74
24	3	Best 10 A.C.	8,10,7	1,2,24,25,26,48,49,50,73,97	10.46
24	3	A.C. >0.7	8,3,6	1	13.72
24	3	A.C. >0.8	9,1,9	1	18.8
24	3	A.C. >0.9	10,9,10	1	18.22
24	3	1 to n	9,8,10	1 to 5	15.31
24	3	1 to n	10,9,7	1 to 15	17.08
24	3	1 to n	10,6,10	1 to 25	12.55

Table 4.22. MAPE values (1176, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	8	1,2,25,49,73	16.12
24	1	Best 7 A.C.	9	1,2,24,25,49,73,97	12.45
24	1	Best 10 A.C.	2	1,2,24,25,26,48,49,50,73,97	16.83
24	1	A.C. >0.7	7	1	16.43
24	1	A.C. >0.8	8	1	18.82
24	1	A.C. >0.9	8	1	19.69
24	1	1 to n	8	1 to 5	17.81
24	1	1 to n	10	1 to 15	14.93
24	1	1 to n	7	1 to 25	16.32

Table 4.23. MAPE values (1176, 2 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	8,8	1,2,25,49,73	18.19
24	2	Best 7 A.C.	9,10	1,2,24,25,49,73,97	19.54
24	2	Best 10 A.C.	9,10	1,2,24,25,26,48,49,50,73,97	18.46
24	2	A.C. >0.7	7,6	1	20.37
24	2	A.C. >0.8	10,8	1	13.08
24	2	A.C. >0.9	1,4	1	16.29
24	2	1 to n	10,8	1 to 5	15.01
24	2	1 to n	8,10	1 to 15	16.65
24	2	1 to n	10,3	1 to 25	14.71

Table 4.24. MAPE values (1176, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	MAPE
24	3	Best 5 A.C.	9,3,6	1,2,25,49,73	15.11
24	3	Best 7 A.C.	6,9,5	1,2,24,25,49,73,97	20.17
24	3	Best 10 A.C.	5,6,7	1,2,24,25,26,48,49,50,73,97	18.24
24	3	A.C. >0.7	7,9,7	1	18.92
24	3	A.C. >0.8	9,9,8	1	16.46
24	3	A.C. >0.9	8,9,8	1	19.45
24	3	1 to n	9,9,6	1 to 5	15.18
24	3	1 to n	9,7,5	1 to 15	10.45
24	3	1 to n	10,7,6	1 to 25	13.12

Table 4.25. MAPE values (1276, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	MAPE
24	1	Best 5 A.C.	4	1,2,24,25,49	25.27
24	1	Best 7 A.C.	8	1,2,3,24,25,26,49	28.68
24	1	Best 10 A.C.	10	1,2,3,4,24,25,26,49,50,73	25.15
24	1	A.C. >0.7	10	1	16.43
24	1	A.C. >0.8	8	1	18.82
24	1	A.C. >0.9	8	1	19.69
24	1	1 to n	9	1 to 5	17.81
24	1	1 to n	6	1 to 15	14.93
24	1	1 to n	6	1 to 25	16.32

Table 4.26. MAPE values (1276, 2 layers, MLP)

Number of Forecast	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	9,8	1,2,24,25,49	25.03
24	2	Best 7 A.C.	9,1	1,2,3,24,25,26,49	24.42
24	2	Best 10 A.C.	10,2	1,2,3,4,24,25,26,49,50,73	16.87
24	2	A.C. >0.7	8,5	1	15.48
24	2	A.C. >0.8	1,9	1	20.16
24	2	A.C. >0.9	7,8	1	23.49
24	2	1 to n	10,9	1 to 5	21.96
24	2	1 to n	7,6	1 to 15	29.47
24	2	1 to n	7,10	1 to 25	32.56

Table 4.27. MAPE values (1276, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	3	Best 5 A.C.	6,6,6	1,2,24,25,49	20.31
24	3	Best 7 A.C.	9,9,6	1,2,3,24,25,26,49	23.26
24	3	Best 10 A.C.	10,9,8	1,2,3,4,24,25,26,49,50,73	23.3
24	3	A.C. >0.7	9,8,5	1	24.11
24	3	A.C. >0.8	10,5,10	1	18.36
24	3	A.C. >0.9	10,8,7	1	21.99
24	3	1 to n	4,8,8	1 to 5	27.35
24	3	1 to n	8,5,2	1 to 15	37.13
24	3	1 to n	7,4,8	1 to 25	26.54

Table 4.28. MAPE values (1376, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	3	1,2,24,25,49	26.32
24	1	Best 7 A.C.	9	1,2,3,24,25,26,49	30.15
24	1	Best 10 A.C.	9	1,2,3,4,24,25,26,49,50,73	17.28
24	1	A.C. >0.7	10	1,2,25	17.68
24	1	A.C. >0.8	6	1	22.26
24	1	A.C. >0.9	8	1	18.52
24	1	1 to n	8	1 to 5	18.19
24	1	1 to n	8	1 to 15	34.34
24	1	1 to n	9	1 to 25	32.93

Table 4.29. MAPE values (1376, 2 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	7,5	1,2,24,25,49	27.54
24	2	Best 7 A.C.	8,9	1,2,3,24,25,26,49	24.77
24	2	Best 10 A.C.	8,10	1,2,3,4,24,25,26,49,50,73	27.43
24	2	A.C. >0.7	10,7	1,2,25	29.52
24	2	A.C. >0.8	7,8	1	26.37
24	2	A.C. >0.9	10,9	1	19.12
24	2	1 to n	6,4	1 to 5	15.26
24	2	1 to n	10,2	1 to 15	36.78
24	2	1 to n	9,8	1 to 25	31.52

Table 4.30. MAPE values (1376, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	MAPE
24	3	Best 5 A.C.	8,8,8	1,2,24,25,49	31.71
24	3	Best 7 A.C.	4,9,5	1,2,3,24,25,26,49	30.71
24	3	Best 10 A.C.	7,8,8	1,2,3,4,24,25,26,49,50,73	28.99
24	3	A.C. >0.7	9,8,6	1,2,25	24.77
24	3	A.C. >0.8	8,10,10	1	19.52
24	3	A.C. >0.9	8,8,8	1	20.56
24	3	1 to n	5,9,4	1 to 5	22.51
24	3	1 to n	8,8,5	1 to 15	31.8
24	3	1 to n	8,7,3	1 to 25	32.92

Table 4.31. MAPE values (1476, 1 layer, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	MAPE
24	1	Best 5 A.C.	1	1,2,24,25,49	33.03
24	1	Best 7 A.C.	7	1,2,3,24,25,26,49	32.73
24	1	Best 10 A.C.	10	1,2,3,4,24,25,26,49,50,73	29.37
24	1	A.C. >0.7	5	1,2,25	29.42
24	1	A.C. >0.8	6	1	24.64
24	1	A.C. >0.9	7	1	27.51
24	1	1 to n	8	1 to 5	32.23
24	1	1 to n	10	1 to 15	29.23
24	1	1 to n	7	1 to 25	32.41

Table 4.32. MAPE values (1476, 2 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	2	Best 5 A.C.	9,8	1,2,24,25,49	31.14
24	2	Best 7 A.C.	9,7	1,2,3,24,25,26,49	36.09
24	2	Best 10 A.C.	9,4	1,2,3,4,24,25,26,49,50,73	32.36
24	2	A.C. >0.7	8,8	1,2,25	29.23
24	2	A.C. >0.8	8,3	1	23.41
24	2	A.C. >0.9	8,6	1	15.3
24	2	1 to n	6,9	1 to 5	35.55
24	2	1 to n	6,10	1 to 15	33.79
24	2	1 to n	10,1	1 to 25	33.37

Table 4.33. MAPE values (1476, 3 layers, MLP)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	3	Best 5 A.C.	9,10,10	1,2,24,25,49	34.12
24	3	Best 7 A.C.	9,7,7	1,2,3,24,25,26,49	32.06
24	3	Best 10 A.C.	5,7,2	1,2,3,4,24,25,26,49,50,73	31.96
24	3	A.C. >0.7	9,9,8	1,2,25	34.26
24	3	A.C. >0.8	7,4,9	1	10.49
24	3	A.C. >0.9	10,3,8	1	26.89
24	3	1 to n	10,9,8	1 to 5	11.21
24	3	1 to n	10,9,3	1 to 15	34.94
24	3	1 to n	10,4,1	1 to 25	34.51

Table 4.34. MAPE values (476, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	*MAPE*
24	150	Best 5 A.C.	50	1,2,25,49,73	10.16
24	150	Best 7 A.C.	25	1,2,25,49,73,97,169	11.02
24	150	Best 10 A.C.	25	1,2,24,25,26,49,73,97,121,169	9.72
24	150	A.C. > 0.7	50	1	9.15
24	150	A.C. > 0.8	100	1	8.9
24	150	A.C. > 0.9	50	1	8.05
24	150	1 to n	50	1 to 5	10.73
24	150	1 to n	25	1 to 15	10.44
24	150	1 to n	50	1 to 25	10.42

Table 4.35. MAPE values (576, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	*MAPE*
24	150	Best 5 A.C.	25	1,2,25,49,73	10.03
24	150	Best 7 A.C.	25	1,2,25,49,73,97,169	11.08
24	150	Best 10 A.C.	50	1,2,25,49,73,97,121,145,169,193	9.59
24	150	A.C. >0.7	100	1	8.95
24	150	A.C. >0.8	50	1	8.93
24	150	A.C. >0.9	25	1	10.77
24	150	1 to n	50	1 to 5	10.04
24	150	1 to n	200	1 to 15	10.88
24	150	1 to n	25	1 to 25	10.81

Table 4.36. MAPE values (676, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	MAPE
24	150	Best 5 A.C.	100	1,2,25,49,73	11.38
24	150	Best 7 A.C.	50	1,2,25,49,73,97,169	9.83
24	150	Best 10 A.C.	25	1,2,24,25,26,49,73,97,169,217	10.38
24	150	A.C. >0.7	50	1	9.95
24	150	A.C. >0.8	25	1	9.36
24	150	A.C. >0.9	200	1	10.16
24	150	1 to n	200	1 to 5	11.25
24	150	1 to n	25	1 to 15	10.35
24	150	1 to n	25	1 to 25	10.22

Table 4.37. MAPE values (776, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	MAPE
24	150	Best 5 A.C.	100	1,2,25,49,73	10.55
24	150	Best 7 A.C.	25	1,2,24,25,49,73,97	11.45
24	150	Best 10 A.C.	100	1,2,24,25,26,49,72,73,97,169	11.10
24	150	A.C. >0.7	25	1	9.7
24	150	A.C. >0.8	100	1	9.73
24	150	A.C. >0.9	200	1	9.13
24	150	1 to n	200	1 to 5	11.09
24	150	1 to n	100	1 to 15	11.23
24	150	1 to n	200	1 to 25	14.94

Table 4.38. MAPE values (876, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	MAPE
24	150	Best 5 A.C.	50	1,2,25,49,73	11.23
24	150	Best 7 A.C.	25	1,2,25,49,73,97,169	10.77
24	150	Best 10 A.C.	50	1,2,24,25,26,49,73,97,121,169	9.75
24	150	A.C. >0.7	25	1	10.64
24	150	A.C. >0.8	50	1	10.06
24	150	A.C. >0.9	200	1	10.13
24	150	1 to n	50	1 to 5	10.78
24	150	1 to n	25	1 to 15	10.94
24	150	1 to n	50	1 to 25	10.65

Table 4.39. MAPE values (976, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	MAPE
24	150	Best 5 A.C.	200	1,2,25,49,73	10.49
24	150	Best 7 A.C.	50	1,2, 25,49,73,97,169	10.65
24	150	Best 10 A.C.	50	1,2,24,25,26,49,50,73,97,169	11.05
24	150	A.C. >0.7	50	1	10.39
24	150	A.C. >0.8	50	1	9.97
24	150	A.C. >0.9	25	1	9.75
24	150	1 to n	200	1 to 5	11.47
24	150	1 to n	100	1 to 15	11.3
24	150	1 to n	25	1 to 25	11.38

Table 4.40. MAPE values (1076, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	*MAPE*
24	150	Best 5 A.C.	200	1,2,25,49,73	10.96
24	150	Best 7 A.C.	50	1,2,24,25,49,73,97	10.93
24	150	Best 10 A.C.	50	1,2,24,25,26,48,49,50,73,97	11.18
24	150	A.C. >0.7	25	1	10.16
24	150	A.C. >0.8	25	1	9.92
24	150	A.C. >0.9	25	1	10.5
24	150	1 to n	50	1 to 5	10.43
24	150	1 to n	25	1 to 15	11.6
24	150	1 to n	25	1 to 25	12.65

Table 4.41. MAPE values (1176, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	*MAPE*
24	150	Best 5 A.C.	25	1,2,25,49,73	11.61
24	150	Best 7 A.C.	100	1,2,25,49,73,97	11.13
24	150	Best 10 A.C.	25	1,2,24,25,26,48,49,50,73,97	10.6
24	150	A.C. >0.7	25	1	10.84
24	150	A.C. >0.8	25	1	9.72
24	150	A.C. >0.9	25	1	10.34
24	150	1 to n	50	1 to 5	10.67
24	150	1 to n	50	1 to 15	10.76
24	150	1 to n	25	1 to 25	12.05

Table 4.42. MAPE values (1276, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	*MAPE*
24	150	Best 5 A.C.	50	1,2,24,25,49	10.13
24	150	Best 7 A.C.	25	1,2,3,24,25,26,49	12.99
24	150	Best 10 A.C.	200	1,2,3,4,24,25,26,49,50,73	11.09
24	150	A.C. >0.7	200	1	9.02
24	150	A.C. >0.8	200	1	10.29
24	150	A.C. >0.9	25	1	11.35
24	150	1 to n	25	1 to 5	11.51
24	150	1 to n	50	1 to 15	11.01
24	150	1 to n	50	1 to 25	10.52

Table 4.43. MAPE values (1376, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	*MAPE*
24	150	Best 5 A.C.	100	1,2,24,25,49	10.71
24	150	Best 7 A.C.	50	1,2,3,24,25,26,49	9.3
24	150	Best 10 A.C.	25	1,2,3,4,24,25,26,49,50,73	17.71
24	150	A.C. >0.7	50	1	10.24
24	150	A.C. >0.8	100	1	8.88
24	150	A.C. >0.9	50	1	8.71
24	150	1 to n	50	1 to 5	9.68
24	150	1 to n	200	1 to 15	11.34
24	150	1 to n	25	1 to 25	14.14

Table 4.44. MAPE values (1476, LSTM)

Number of Frc.	Number of Epo.	Delay Options	Hidden Units	Delays	*MAPE*
24	150	Best 5 A.C.	50	1,2,24,25,49	10.42
24	150	Best 7 A.C.	50	1,2,3,24,25,26,49	9.52
24	150	Best 10 A.C.	100	1,2,3,4,24,25,26,49,50,73	10.51
24	150	A.C. >0.7	50	1,2,25	9.22
24	150	A.C. >0.8	100	1	8.66
24	150	A.C. >0.9	100	1	8.06
24	150	1 to n	50	1 to 5	9.44
24	150	1 to n	50	1 to 15	9.3
24	150	1 to n	50	1 to 25	11.24

Table 4.45. MAPE values (476, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	150	Best 5 A.C.	1,2,25,49,73	4.88
24	150	Best 7 A.C.	1,2,25,49,73,97,169	5.91
24	150	Best 10 A.C.	1,2,24,25,26,49,73,97,121,169	7.77
24	150	A.C. >0.7	1	5.34
24	150	A.C. >0.8	1	9.69
24	150	A.C. >0.9	1	4.12
24	150	1 to n	1 to 5	5.95
24	150	1 to n	1 to 15	5.03
24	150	1 to n	1 to 25	6.45

Table 4.46. MAPE values (576, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,25,49,73	6.64
24	100	Best 7 A.C.	1,2,25,49,73,97,169	3.8
24	100	Best 10 A.C.	1,2,25,49,73,97,121,145,169	4.52
24	100	A.C. >0.7	1	7.8
24	100	A.C. >0.8	1	5.73
24	100	A.C. >0.9	1	3.76
24	100	1 to n	1 to 5	5.2
24	100	1 to n	1 to 15	7.87
24	100	1 to n	1 to 25	4.86

Table 4.47. MAPE values (676, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,25,49,73	8.68
24	100	Best 7 A.C.	1,2,25,49,73,97,169	6.48
24	100	Best 10 A.C.	1,2,24,25,26,49,73,97,169,217	4.08
24	100	A.C. >0.7	1	4.79
24	100	A.C. >0.8	1	5.42
24	100	A.C. >0.9	1	4.89
24	100	1 to n	1 to 5	4.9
24	100	1 to n	1 to 15	5.28
24	100	1 to n	1 to 25	5.69

Table 4.48. MAPE values (776, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,25,49,73	6.28
24	100	Best 7 A.C.	1,2,24,25,49,73,97	7.05
24	100	Best 10 A.C.	1,2,24,25,26,49,72,73,97,169	7.8
24	100	A.C. >0.7	1	5.59
24	100	A.C. >0.8	1	5.98
24	100	A.C. >0.9	1	5.63
24	100	1 to n	1 to 5	6.38
24	100	1 to n	1 to 15	5.53
24	100	1 to n	1 to 25	5.98

Table 4.49. MAPE values (876, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,25,49,73	5.96
24	100	Best 7 A.C.	1,2,25,49,73,97,169	9.32
24	100	Best 10 A.C.	1,2,24,25,26,49,73,97,121,169	9.44
24	100	A.C. >0.7	1	9.15
24	100	A.C. >0.8	1	6.64
24	100	A.C. >0.9	1	5.57
24	100	1 to n	1 to 5	5.35
24	100	1 to n	1 to 15	6.16
24	100	1 to n	1 to 25	6.25

Table 4.50. MAPE values (976, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,25,49,73	5.46
24	100	Best 7 A.C.	1,2,25,49,73,97,169	5.67
24	100	Best 10 A.C.	1,2,24,25,26,49,50,73,97,169	6.82
24	100	A.C. >0.7	1	5.26
24	100	A.C. >0.8	1	4.19
24	100	A.C. >0.9	1	5.68
24	100	1 to n	1 to 5	5.94
24	100	1 to n	1 to 15	7.23
24	100	1 to n	1 to 25	6.37

Table 4.51. MAPE values (1076, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,25,49,73	5.7
24	100	Best 7 A.C.	1,2,24,25,49,73,97	6.23
24	100	Best 10 A.C.	1,2,24,25,26,48,49,50,73,97	8.48
24	100	A.C. >0.7	1	5.72
24	100	A.C. >0.8	1	4.51
24	100	A.C. >0.9	1	4.85
24	100	1 to n	1 to 5	5.04
24	100	1 to n	1 to 15	6.13
24	100	1 to n	1 to 25	5.09

Table 4.52. MAPE values (1176, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,25,49,73	6.04
24	100	Best 7 A.C.	1,2,24,25,49,73,97	4.6
24	100	Best 10 A.C.	1,2,24,25,26,48,49,50,73,97	6.5
24	100	A.C. >0.7	1	4.5
24	100	A.C. >0.8	1	4.44
24	100	A.C. >0.9	1	7.17
24	100	1 to n	1 to 5	5.06
24	100	1 to n	1 to 15	6.38
24	100	1 to n	1 to 25	4.61

Table 4.53. MAPE values (1276, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,24,25,49	6.59
24	100	Best 7 A.C.	1,2,3,24,25,26,49	4.27
24	100	Best 10 A.C.	1,2,3,4,24,25,26,49,50,73	5.01
24	100	A.C. >0.7	1	4.35
24	100	A.C. >0.8	1	4.63
24	100	A.C. >0.9	1	4.81
24	100	1 to n	1 to 5	5.54
24	100	1 to n	1 to 15	4.73
24	100	1 to n	1 to 25	6.39

Table 4.54. MAPE values (1376, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,24,25,49	6.52
24	100	Best 7 A.C.	1,2,3,24,25,26,49	5.27
24	100	Best 10 A.C.	1,2,3,4,24,25,26,49,50,73	5.06
24	100	A.C. >0.7	1,2,25	9.1
24	100	A.C. >0.8	1	6.2
24	100	A.C. >0.9	1	4.89
24	100	1 to n	1 to 5	4.04
24	100	1 to n	1 to 15	4.99
24	100	1 to n	1 to 25	6.08

Table 4.55. MAPE values (1476, CNN)

Number of Frc.	Number of Epo.	Delay Options	Delays	*MAPE*
24	100	Best 5 A.C.	1,2,24,25,49	5.01
24	100	Best 7 A.C.	1,2,3,24,25,26,49	6.82
24	100	Best 10 A.C.	1,2,3,4,24,25,26,49,50,73	6.2
24	100	A.C. >0.7	1,2,25	7.31
24	100	A.C. >0.8	1	4.02
24	100	A.C. >0.9	1	4.34
24	100	1 to n	1 to 5	4.71
24	100	1 to n	1 to 15	4.91
24	100	1 to n	1 to 25	5.77

Table 4.56. MAPE values (476, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	10	1,2,25,49,73	12.14
24	1	Best 7 A.C.	5	1,2,25,49,73,97,169	10.18
24	1	Best 10 A.C.	9	1,2,24,25,26,49,73,97,121,169	10.73
24	1	A.C. >0.7	8	1	18.02
24	1	A.C. >0.8	9	1	14.41
24	1	A.C. >0.9	4	1	20.08
24	1	1 to n	2	1 to 5	15
24	1	1 to n	8	1 to 15	14.16
24	1	1 to n	10	1 to 25	10.88

Table 4.57. MAPE values (576, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	9	1,2,25,49,73	9.81
24	1	Best 7 A.C.	7	1,2,25,49,73,97,169	16.43
24	1	Best 10 A.C.	8	1,2,25,49,73,97,121,145,169,193	14.38
24	1	A.C. >0.7	9	1	19.46
24	1	A.C. >0.8	6	1	12.34
24	1	A.C. >0.9	6	1	17.97
24	1	1 to n	9	1 to 5	13.02
24	1	1 to n	6	1 to 15	14.63
24	1	1 to n	24	1 to 25	13

Table 4.58. MAPE values (676, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	9	1,2,25,49,73	15.49
24	1	Best 7 A.C.	9	1,2,25,49,73,97,169	10.75
24	1	Best 10 A.C.	4	1,2,24,25,26,49,73,97,169,217	14.58
24	1	A.C. >0.7	7	1	8.7
24	1	A.C. >0.8	24	1	17.38
24	1	A.C. >0.9	10	1	30.6
24	1	1 to n	7	1 to 5	17.38
24	1	1 to n	8	1 to 15	22.79
24	1	1 to n	10	1 to 25	21.37

Table 4.59. MAPE values (776, RNN)

Number of Frc.	Layers	Delay Options		Delays	*MAPE*
24	1	Best 5 A.C.	9	1,2,25,49,73	17.82
24	1	Best 7 A.C.	7	1,2,24,25,49,73,97	26.67
24	1	Best 10 A.C.	5	1,2,24,25,26,49,72,73,97,169	14.29
24	1	A.C. >0.7	5	1	14.55
24	1	A.C. >0.8	10	1	26.52
24	1	A.C. >0.9	7	1	18.06
24	1	1 to n	6	1 to 5	20.85
24	1	1 to n	3	1 to 15	18.04
24	1	1 to n	7	1 to 25	20.93

Table 4.60. MAPE values (876, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	9	1,2,25,49,73	25.94
24	1	Best 7 A.C.	8	1,2,25,49,73,97,169	18.93
24	1	Best 10 A.C.	7	1,2,24,25,26,49,73,97,121,169	19.28
24	1	A.C. >0.7	7	1	21.18
24	1	A.C. >0.8	6	1	16.53
24	1	A.C. >0.9	10	1	28.16
24	1	1 to n	10	1 to 5	23.03
24	1	1 to n	2	1 to 15	21.01
24	1	1 to n	4	1 to 25	17.39

Table 4.61. MAPE values (976, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	10	1,2,25,49,73	12.27
24	1	Best 7 A.C.	10	1,2,25,49,73,97,169	20.28
24	1	Best 10 A.C.	7	1,2,24,25,26,49,50,73,97,169	14.65
24	1	A.C. >0.7	6	1	16.92
24	1	A.C. >0.8	9	1	19.76
24	1	A.C. >0.9	8	1	33.63
24	1	1 to n	7	1 to 5	27.41
24	1	1 to n	5	1 to 15	18.54
24	1	1 to n	3	1 to 25	18.58

Table 4.62. MAPE values (1076, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	6	1,2,25,49,73	25.45
24	1	Best 7 A.C.	8	1,2,24,25,49,73,97	19.99
24	1	Best 10 A.C.	7	1,2,24,25,26,48,49,50,73,97	19.47
24	1	A.C. >0.7	5	1	21.18
24	1	A.C. >0.8	6	1	18.96
24	1	A.C. >0.9	10	1	20.34
24	1	1 to n	6	1 to 5	20.84
24	1	1 to n	2	1 to 15	20.06
24	1	1 to n	2	1 to 25	20.35

Table 4.63. MAPE values (1176, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	9	1,2,25,49,73	21.73
24	1	Best 7 A.C.	7	1,2,24,25,49,73,97	22.96
24	1	Best 10 A.C.	9	1,2,24,25,26,48,49,50,73,97	19.10
24	1	A.C. >0.7	10	1	23.39
24	1	A.C. >0.8	6	1	23.38
24	1	A.C. >0.9	8	1	23.29
24	1	1 to n	3	1 to 5	22.35
24	1	1 to n	6	1 to 15	25.02
24	1	1 to n	9	1 to 25	21.89

Table 4.64. MAPE values (1276, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	6	1,2,24,25,49	27.33
24	1	Best 7 A.C.	10	1,2,3,24,25,26,49	30.7
24	1	Best 10 A.C.	6	1,2,3,4,24,25,26,49,50,73	24.33
24	1	A.C. >0.7	9	1	26.02
24	1	A.C. >0.8	4	1	30.16
24	1	A.C. >0.9	7	1	28.6
24	1	1 to n	9	1 to 5	35.66
24	1	1 to n	9	1 to 15	33.06
24	1	1 to n	7	1 to 25	30.01

Table 4.65. MAPE values (1376, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	4	1,2,24,25,49	29.44
24	1	Best 7 A.C.	3	1,2,3,24,25,26,49	28.02
24	1	Best 10 A.C.	2	1,2,3,4,24,25,26,49,50,73	25.24
24	1	A.C. >0.7	5	1,2,25	29.7
24	1	A.C. >0.8	10	1	28.49
24	1	A.C. >0.9	5	1	28.09
24	1	1 to n	8	1 to 5	28.2
24	1	1 to n	7	1 to 15	27.94
24	1	1 to n	7	1 to 25	30

Table 4.66. MAPE values (1476, RNN)

Number of Frc.	Layers	Delay Options	Neurons	Delays	*MAPE*
24	1	Best 5 A.C.	10	1,2,24,25,49	32.4
24	1	Best 7 A.C.	4	1,2,3,24,25,26,49	32.73
24	1	Best 10 A.C.	7	1,2,3,4,24,25,26,49,50,73	29.35
24	1	A.C. >0.7	9	1,2,25	34.84
24	1	A.C. >0.8	7	1	29.13
24	1	A.C. >0.9	10	1	27.39
24	1	1 to n	7	1 to 5	29.82
24	1	1 to n	9	1 to 15	29.68
24	1	1 to n	9	1 to 25	32.83

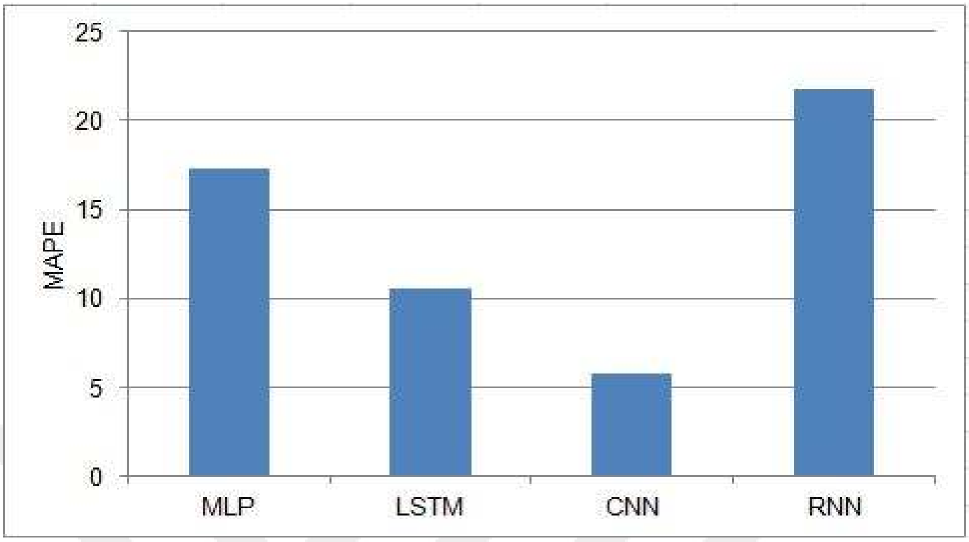

Figure 4.5. *MAPE*s in average for feedback delay options with MLP and other prediction models

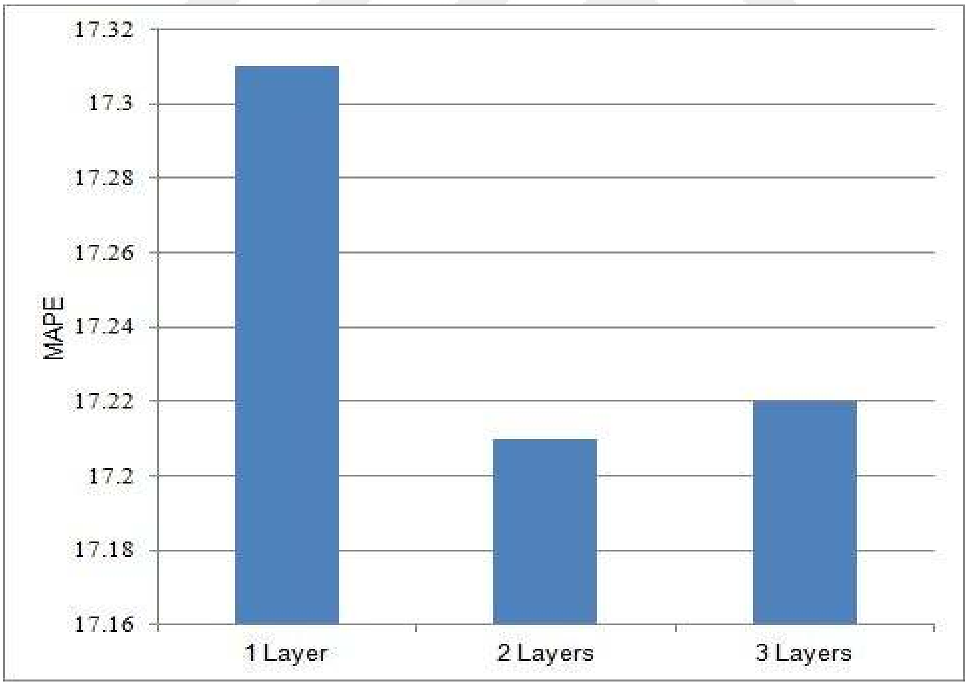

Figure 4.6. The comparison of the number of hidden layers for MLP-based prediction models

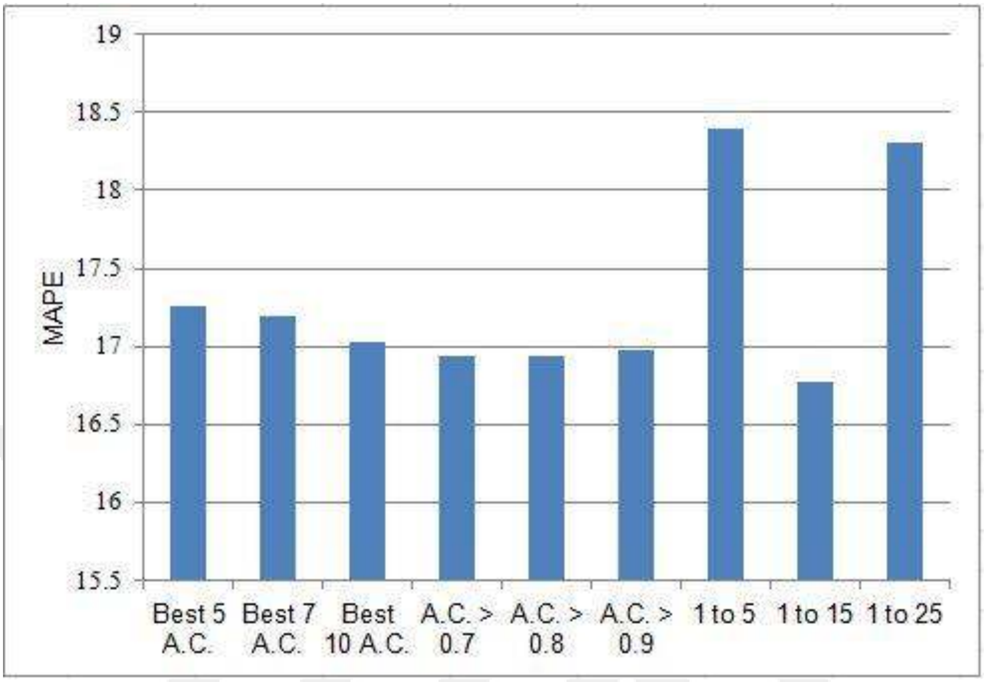

Figure 4.7. *MAPE*s in average for feedback delay options with one layer prediction models

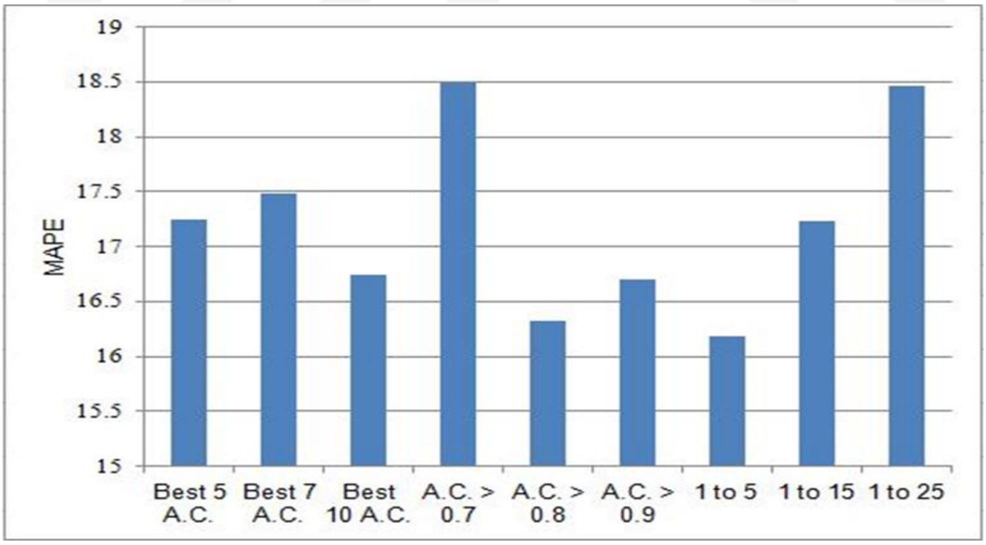

Figure 4.8. *MAPE*s in average for feedback delay options with two layers prediction models

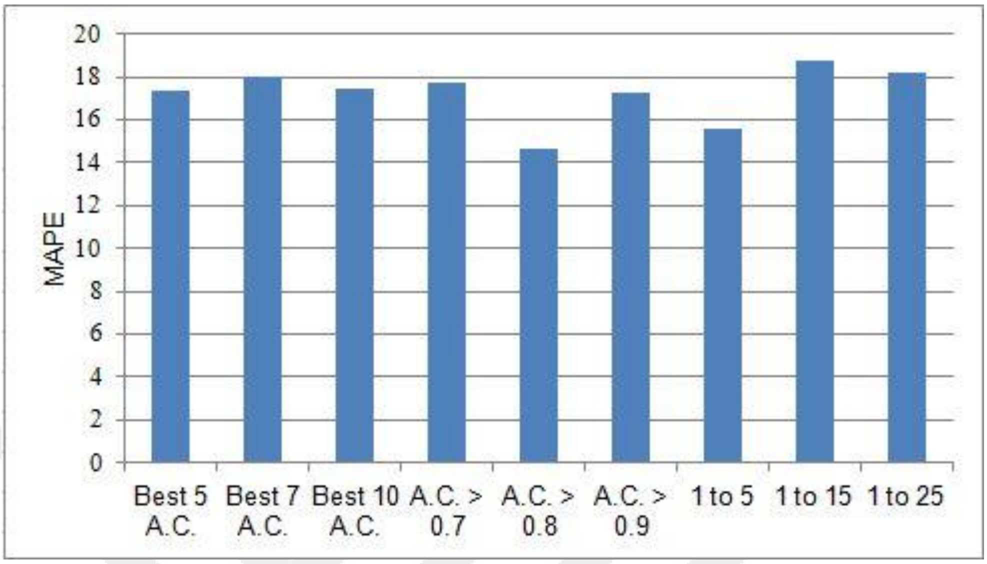

Figure 4.9. *MAPE*s in average for feedback delay options with three layers prediction models

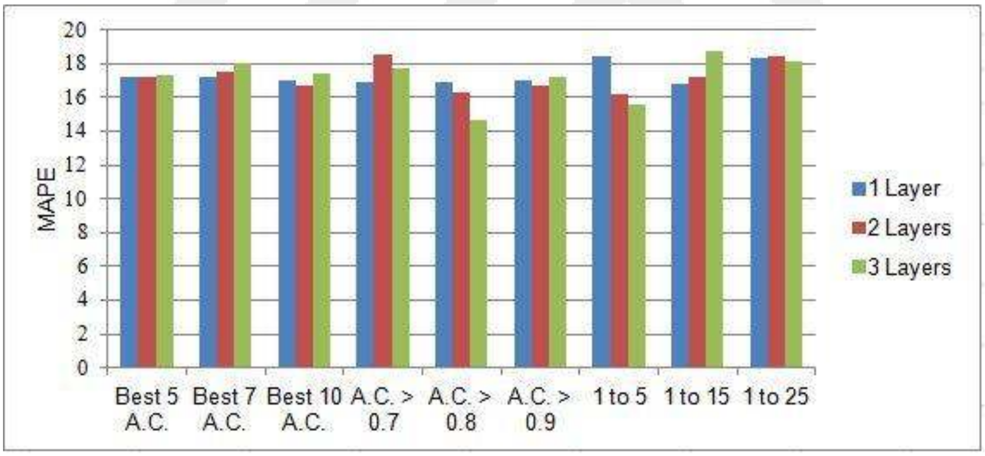

Figure 4.10. *MAPE*s in average for feedback delay options with layers prediction models

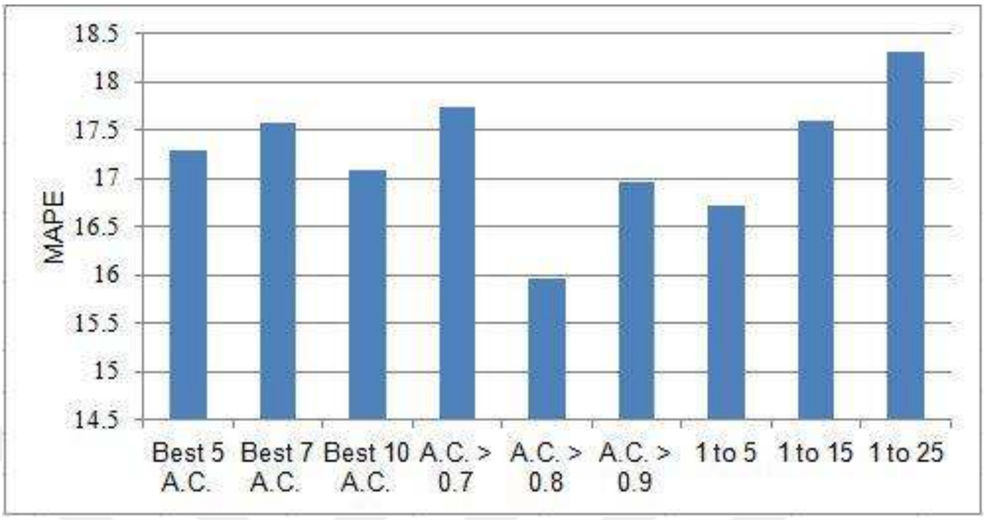

Figure 4.11. *MAPE*s in average for MLP-based models with feedback delay options

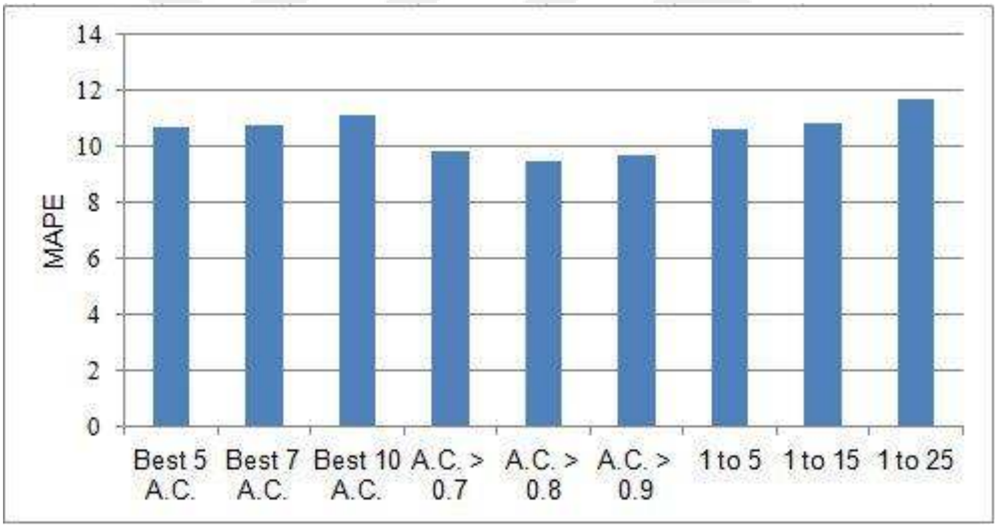

Figure 4.12. *MAPE*s in average for LSTM-based models with feedback delay options

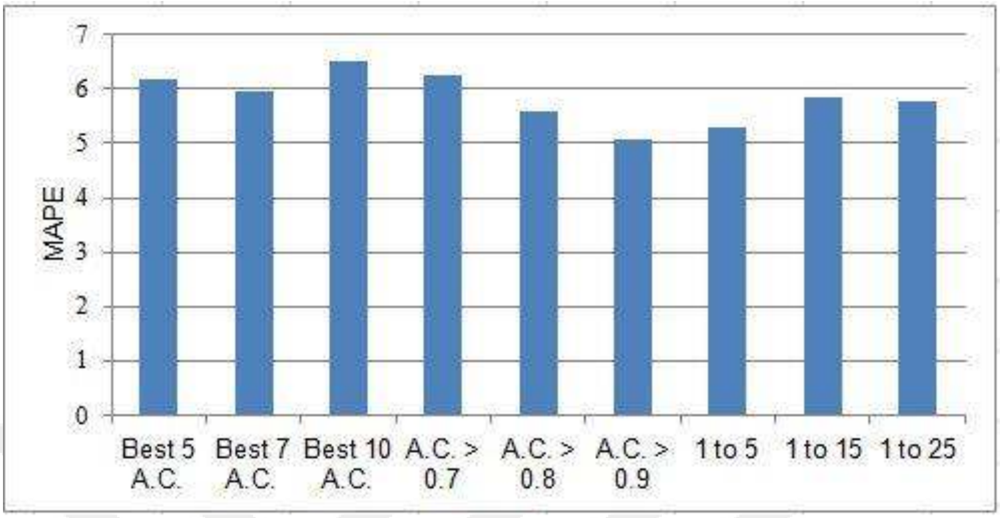

Figure 4.13. *MAPE*s in average for CNN-based models with feedback delay options

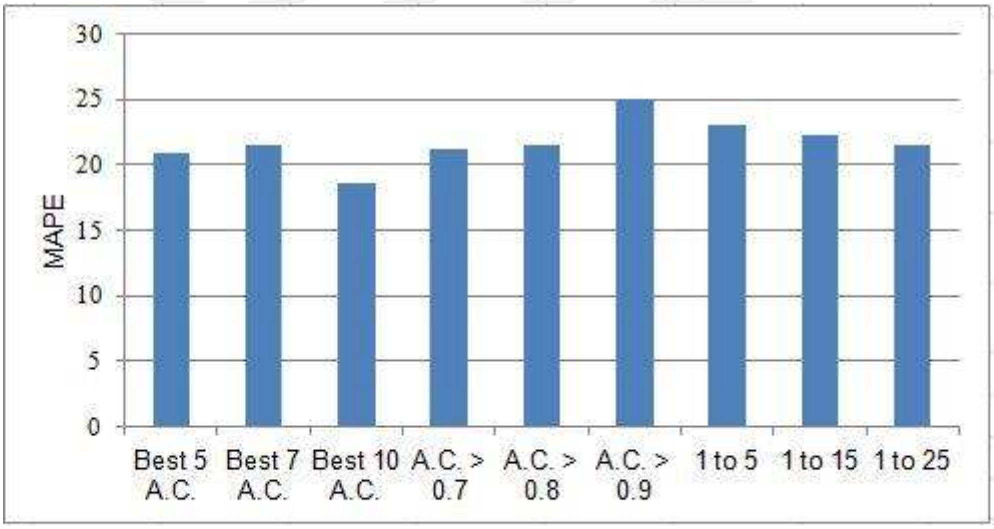

Figure 4.14. *MAPE*s in average for RNN-based models with feedback delay options

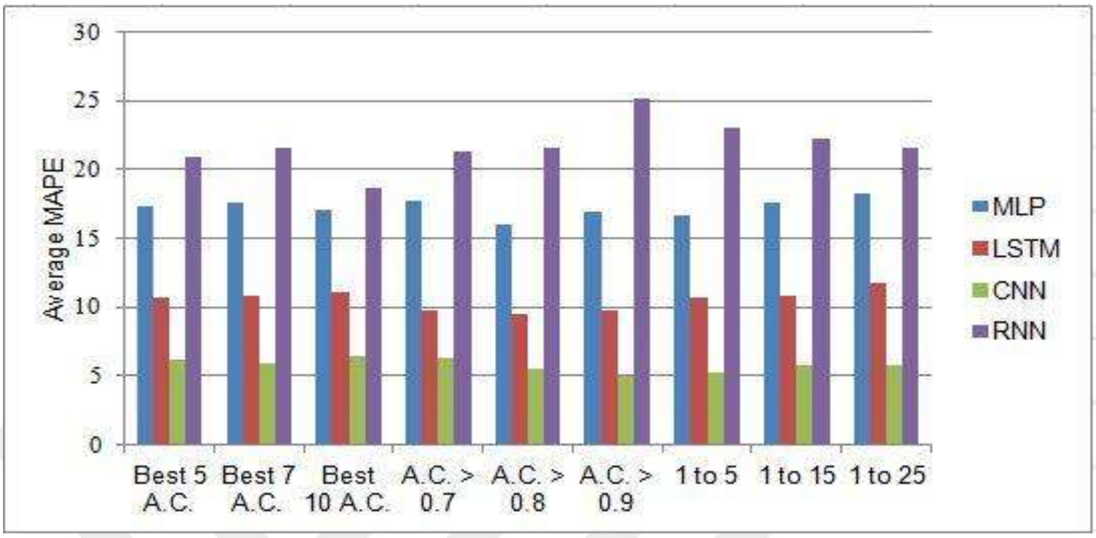

Figure 4.15. Average *MAPE*'s of the prediction models with feedback delay options

4.1. General Discussion of the Results

The results obtained in this study show that CNN and LSTM based prediction models perform better than MLP and RNN based prediction models compared to general average mape values. CNN, LSTM, MLP and RNN are the overall ranking of the highest accuracy obtained in forecasting models developed using time delays for forecasting performances based on MAPEs. In more details:

- In this study, 24 estimations are applied in all forecasting models in order to generate hourly market clearing price 1 day forecasts. The results obtained in this thesis are based on the data sets of the market clearing price values from 500 to 1500. The results, parameters and values obtained from the machine and deep learning methods used in this study are presented in tables and graphs. In this respect, a total of 66 tables and 11 graphs were created. Time delays and autocorrelation optimizations are crucial for the neural networks used in machine and deep learning methods in order to obtain the best performance and produce the most accurate estimation of the estimation models based on the obtained MAPE values.

- In this study, some optimizations are used to determine feedback delays in forecasting models. The autocorrelation value is greater than 0.7, 0.8 and 0.9, the highest 5, 7 and 10 autocorrelation values and the autocorrelation values range from 1 to 5, 15 and 25 respectively. According to the results, it was not observed that changing the feedback delays used in the prediction models significantly decreased or increased the MAPE values.
- The average MAPE obtained from CNN-based forecasting models has a lower average MAPE value than other applied machine learning and deep learning methods when evaluated based on the average MAPE results obtained from market clearing price estimates. The ranking of the applied machine learning and deep learning methods in terms of performance considering the average lowest MAPEs can be evaluated as CNN, LSTM, MLP and RNN for market clearing price estimation. The values obtained from the market clearing price estimates based on the average MAPEs based on their performances are 5.82 for CNN, 10.54 for LSTM, 17.25 for MLP and 21.77 for RNN, respectively.
- In MLP prediction models, the networks formed include one, two or three hidden layers. According to the obtained average MAPE values, it is 17.31 for one hidden layer, 17.21 for two hidden layers and 17.22 for three hidden layers. According to these results, it is seen that the estimates obtained with two hidden layers on average are more accurate. However, when evaluated together with other hidden layers, it is seen that there is no significant difference in forecast performance. In MLP estimation models, the lowest MAPE values obtained for one, two and three hidden layers are 7.21, 7.14 and 7.22, respectively. The

number of neurons used in these prediction models is 9 for a hidden layer, 7 and 8 with two hidden layers, and 9,7 and 7 with three hidden layers, respectively. In addition, the most efficient optimal neuron numbers vary according to the performance of the hidden layers in the prediction models made with MLP.

- When optimizing the time delays used in the MLP, the average MAPE values for 1 hidden layer range between 16.77 and 18.39, and these values are observed when the autocorrelation values are from 1 to 15 and the autocorrelation values are from 1 to 25. Average MAPE values for the 2 hidden layers ranged between 16.18 and 18.49, and these values were obtained when the autocorrelation values were from 1 to 5 and the autocorrelation threshold is greater than 0.7. Average MAPE values for the 3 hidden layers ranged from 14.66 to 18.78, and these values were obtained when the the autocorrelation threshold was greater than 0.8 and the autocorrelation values were from 1 to 15. According to the average MAPE values for the 1,2 and 3 hidden layers, the best mean MAPE value is 15.56 and the worst mean MAPE value is 18.78. According to these results, it is seen that autocorrelation values and related delay values are very important factors in producing the best performance models with the highest performance.
- The average MAPE values obtained while optimizing the time delays used in the applied MLP, LSTM, CNN and RNN machine and deep learning methods ranged between 15.97 and 18.31. These two values were obtained when the autocorrelation threshold was greater than 0.8 and the autocorrelation values were from 1 to 25. The mean MAPE values obtained for LSTM ranged between 9.49 and 11.72, and these two values were obtained when the autocorrelation threshold was greater than 0.8 and the autocorrelation values were from 1 to 25. The

mean MAPE values obtained for CNN ranged between 5.06 and 6.51, and these two values were obtained when the autocorrelation threshold was greater than 0.9 and the top 10 autocorrelation values were used. The mean MAPE values obtained for RNN ranged between 18.67 and 25.11, and these two values occurred when the top 10 autocorrelation values were used and the autocorrelation threshold was greater than 0.9. Based on these results, the lowest mean MAPE value obtained from prediction models was 5.06 and obtained from CNN method, and the highest mean MAPE value was 25.11 and obtained from the RNN method. When these results are taken into consideration, the highest performance according to the average MAPE values are CNN, LSTM, MLP and RNN respectively. According to these results, it is vitally important which machine and deep learning method will be used to make the most accurate prediction and develop the most accurate prediction models.

- In this thesis, the results were obtained by increasing the market clearing price data set from the last 500 to 1500 by 100 and learning for them. The lowest MAPE values obtained from each of the applied machine and deep learning methods were 5.06 with CNN, 7.14 with MLP, 8.05 with LSTM, and 8.7 with RNN, respectively. The learning amounts used from this lowest MAPE values dataset are the last 500 of the dataset for MLP, the last 500 of dataset for LSTM, the last 700 of dataset for RNN, and the last 1200 of dataset for CNN. When the amount of learning applied from the dataset used is evaluated, it is seen that it is less in MLP and LSTM and it is more in CNN. In order to obtain more accurate and acceptable estimates based on these results, it has been proved that the amount of learning in the dataset can be obtained with the lowest MAPE values at different values in the methods.

5. CONCLUSION

Today, it is very popular to use machine and deep learning methods in predicting the future. In this thesis, the market clearing price of electricity is estimated by using machine learning and deep learning methods. The machine learning and deep learning methods used are MLP, LSTM, CNN and RNN. The performance of the machine learning and deep learning methods used was compared and evaluated by calculating the mean absolute error values. In this thesis, the estimated market clearing price data sets for the period 01.01.2016 - 01.01.2018 were provided from the website (https://sparlik.epias.com.tr). By using market clearing price datas, 24 estimations have been made and estimation models have been produced based on time delays and autocorrelation values. In the generated estimation models, learning has been made by increasing the parts of the dataset from the last 500 to 1500 by 100. The prediction models developed contain parameters appropriate to the machine and deep learning method whichever machine and deep learning method was used. Different error rates were obtained by using time delay and autocorrelation values. 66 tables and 594 different models were produced from prediction models. When the average MAPE values obtained are evaluated, it is observed that the amount of teaching used from the highest performances dataset is different. Therefore, the amount of learning to be used in the dataset has been proved to be a very important parameter in order to obtain more stable and lower error rates than the prediction models. According to the results obtained from the models, it has been proved that the LSTM, MLP, CNN and RNN machine and deep learning methods can be used in an acceptable degree of accuracy of the electricity market clearing price.

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CURRICULUM

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