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ELECTRICITY PRICE FORECASTING IN TURKISH DAY-AHEAD MARKET VIA DEEP LEARNING TECHNIQUES*

DERİN ÖĞRENME TEKNİKLERİYLE TÜRKİYE GÜN ÖNCESİ PİYASASINDA ELEKTRİK FİYAT TAHMİNİ

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Abstract

Day-Ahead Market offers electricity market participants the opportunity to trade electricity one day ahead of real-time. For each hour, a separate Market Clearing Price is created in Day-Ahead Market. This study aims to predict the hourly Market Clearing Price using deep learning techniques. In this context, 24-hour Market Clearing Prices were forecasted with MLP, CNN, LSTM, and GRU. LSTM had the best average forecasting performance with an 8.15 MAPE value, according to the results obtained. MLP followed the LSTM with 8.44 MAPE, GRU with 8.72 MAPE, and CNN with 9.27 MAPE. In the study, the provinces where the power plants producing with renewable resources are dense were selected for meteorological variables. It is expected that the trend towards electricity generation with renewable resources will increase in the future. In this context, it is thought important for market participants to consider the factors that may affect the production with these resources in the electricity price forecasting.

Keywords: Day-Ahead Market, Price Forecasting, Market Clearing Price, Deep Learning.

Öz

Gün Öncesi Piyasası, elektrik piyasası katılımcılarına gerçek zamandan bir gün öncesinde ticaret yapma imkânı sunan bir piyasadır. Gün Öncesi Piyasasında her saat için ayrı bir Piyasa Takas Fiyatı oluşturulmaktadır. Bu çalışmada, saatlik Piyasa Takas Fiyatının derin öğrenme teknikleri kullanılarak tahmin edilmesi amaçlanmıştır. Bu doğrultuda MLP, CNN, LSTM ve GRU modelleri ile 24 saatlik Piyasa Takas Fiyatı tahmin edilmiştir. Elde edilen sonuçlara göre, LSTM 8,15 MAPE değeri ile en iyi ortalama tahmin performansına sahip olmuştur. LSTM'i 8,44 MAPE değeri ile MLP, 8,72 MAPE değeri ile GRU ve 9,27 MAPE değeri ile CNN takip izlemiştir. Bu çalışmada kullanılan meteorolojik değişkenler için yenilebilir kaynaklarla üretim yapan santrallerin yoğun olduğu iller seçilmiştir. Yenilenebilir kaynaklarla elektrik üretimine olan eğilimin gelecekte daha da artması beklenmektedir. Bu bağlamda, piyasa katılımcıları için elektrik fiyat tahmininde bu kaynaklarla gerçekleşen üretimi etkileyebilecek faktörlerin göz önüne alınmasının önemli olduğu düşünülmektedir.

Anahtar Kelimeler: Gün Öncesi Piyasası, Fiyat Tahmini, Piyasa Takas Fiyatı, Derin Öğrenme.

GENİŞLETİLMİŞ ÖZET

Çalışmanın Amacı

Bu çalışmanın amacı, EPİAŞ bünyesinde işletilen ve elektrik piyasası katılımcılarına gerçek zamandan bir gün öncesinde ticaret yapma imkânı sunan Gün Öncesi Piyasası elektrik fiyatlarının derin öğrenme teknikleri ile tahmin edilmesidir.

Araştırma Soruları

Derin öğrenme tekniklerini kullanarak, Gün Öncesi Piyasası'nda işlem yapan piyasa katılımcılarının teklif stratejisi geliştirme ve üretim/tedarik planlaması yapmada bir araç olarak kullanabileceği yüksek performanslı tahmin sonuçları elde edilebilir mi?

Literatür Araştırması

Elektrik piyasalarının serbestleşmesi ile elektrik ticareti rekabetçi bir piyasa yapısında gerçekleşmeye başlamıştır. Bu bağlamda EPİAŞ bünyesinde işlem görmekte olan Gün Öncesi Piyasası, piyasa katılımcılarına gerçek zamandan bir gün öncesinde saat bazında ticaret yapma imkânı sunmakta ve piyasa katılımcıları için gerek teklif stratejisi oluşturma gerekse de üretim/tedarik planlaması yapma noktasında bu piyasada oluşan Piyasa Takas Fiyatı'nın tahmin edilmesi önem arz etmektedir. Bu durum, araştırmacıların PTF tahminine olan ilgisini artırmakta ve istatistiki yöntemler ve yapay zekâ modelleri başta olmak üzere çeşitli modeller ile PTF tahmini üzerine çalışmalar yapılmaktadır. İstatistiksel yöntemlerden ARMA yönteminin çeşitli formları (ARMA, ARIMA, SARIMA, ARMAX, ARIMAX, SARIMAX vb.) literatürde elektrik fiyat tahmini için sıklıkla kullanılmaktadır. Ayrıca, elektrik fiyatlarının volatilite yapısını modelleme ARCH ailesi modelleri de araştırmacılar tarafından tercih edilmektedir. Cuaresma vd. (2004), Weron ve Misiorek (2006) ve Contreras vd. (2003) ARMA modelinin çeşitli formalarını elektrik fiyat tahmininde kullanmışlardır. Cervone vd. (2014) ise hem ARMA hem de GARCH modeli ile elektrik fiyatlarını tahmin etmiş ve GARCH modeli ile daha yüksek performanslı sonuçlar elde etmişlerdir. Öte yandan, Yang vd. (2017), son yıllarda elektrik fiyat tahmininde yapay zeka modellerinin araştırmacıların ilgisini çektiğini belirtmektedirler. Yang vd. (2017)'e göre, yapay zeka modelleri ağırlıkları ayarlayabilmesinden dolayı elektrik fiyatlarının doğrusal olmama ve dinamik olma gibi karakteristik özelliklerini yakalamada daha başarılıdır. Bu bağlamda Lago vd. (2018), elektrik fiyatlarını tahmin etmek için 27 farklı model kurmuş ve yapay zeka yöntemlerinin istatistiki yöntemlere göre daha yüksek performanslı tahmin sonuçları ürettiği sonucuna ulaşmışlardır. Literatüde zaman zaman istatiski yöntemler ve yapay zeka modelleri ile hibrit modeller oluşturularak elektrik fiyatı tahmi de yapılmaktadır. Chaabane (2014), hibrit bir model olarak ARFIMA-ANN modelini kullanıp elektrik fiyatı tahmininde bulunmuştur. Yapay zeka modellerinden özellikle derin öğrenme teknikleri ile elektrik fiyatı tahminin yapıldığı çalışmalar literatürde ağırlık kazanmaktadır. Li ve Becker (2021), Bento vd. (2018), Uğurlu vd. (2018), Guo vd. (2020), Xie vd. (2018), Huang vd. (2020), Kuo ve Huang (2018), Zhou vd. (2019), Keynia (2012) gibi birçok çalışmada ANN, CNN, LSTM, GRU, CNN-LSTM, ConvLSTM gibi derin öğrenme teknikleri ile elektrik fiyatlarının tahmin edildiği görülmektedir. Örneği çoğaltılabilecek birçok çalışmada, farklı yapay zekâ modelleri ile farklı periyotlar için farklı tahmin performansları elde edilmiştir. Bu çalışmada, yenilenebilir enerji kaynakları ile elektrik üretiminin yoğun olduğu illerdeki meteorolojik veriler dahil edilerek kurulan derin öğrenme modelleri ile elde edilen sonuçların literatüre katkı sağlaması beklenmektedir.

Yöntem

Çalışmada PTF tahmini için MLP, CNN, LSTM ve GRU modelleri kullanılmıştır. Veri seti üç bölüme ayrılarak, ilk aşamada her bir model 13.06.2016-04.10.2020 dönemini kapsayan veriler ile eğitilmiş ve eğitilen modellerin 05.10.2020-28.02.2021 dönemini kapsayan veriler üzerinde doğrulaması yapılmıştır. İkinci aşamada ise, doğrulaması yapılan modeller veri setinin başlangıcından tahmin edilecek günün bir gün öncesine kadar olan veriler ile eğitilerek test dönemindeki her bir gün için modellerin 24 saatlik tahmin performansları elde edilmiştir. Modellerin eğitimi için PTF'nin yanı sıra, haftanın günleri ve resmî tatiller, gerçek zamanlı tüketim, hidroelektrik santral üretim miktarı, sistem marjinal fiyatı, yük tahmin planı, rüzgâr hızı ve sıcaklık olmak 7 adet dışsal değişken kullanılmıştır.

Sonuç ve Değerlendirme

Çalışmada, test dönemi için 24 saatlik PTF'nin tahminine yönelik kurulan MLP modeli ile gün bazında 4,00 ile 16,01 aralığında MAPE değerleri elde edilirken, CNN modeli ile 4,05 ile 16,38 aralığında, LSTM modeli ile 2,38 ile 19,40 aralığında ve GRU modeli ile 4,15 ile 18,61 aralığında MAPE değerleri elde edilmiştir. 28 günün ortalaması alındığında LSTM 8,15 MAPE değeri ile en iyi tahmin performansını gösteren model olmuştur. LSTM'i 8,44 MAPE değeri ile MLP, 8,72 MAPE değeri ile GRU ve 9,27 MAPE değeri ile CNN izlemiştir. 28 günlük tahmin sonuçlarının dağılımda da LSTM modeli %10 sapma değerinin altındaki 23 günlük tahmin ile en iyi performansı gösteren model olmuştur. Çalışmada kullanılan 4 model ile yapılan 112 tahminin 15'i %5'in altında sapma değerine sahipken, 65'i %5 ile %10 arasında, 24'ü %10 ile %15 arasında, 8'i de %15 ile %20 arasında sapma göstermiştir. Bu anlamda, elde edilen tahmin sonuçlarının yüksek isabetli ve iyi tahmin sınırları içerisinde gerçekleştiğini söylemek mümkündür. Çalışmada, elektrik fiyatları üzerinde etkili olabileceği düşünülen rüzgâr ve güneş enerjisi için bu kaynaklarla üretim yapan santrallerin kurulu gücünün en yüksek olduğu illere odaklanılmış ve bu illerdeki istasyonlardan elde edilen veriler modellere dahil edilmiştir. Yenilenebilir kaynaklarla üretimin artış eğiliminde olduğu göz önüne alınırsa, piyasa katılımcılarının elektrik fiyat tahmininde yenilenebilir kaynaklarla gerçekleşecek üretim üzerinde etkisi olabilecek faktörlere odaklanmasının faydalı olabileceği düşünülmektedir.

1. INTRODUCTION

In the electricity markets, which mainly were in public monopoly before liberalization, the activities from the generation of electricity to the delivery to end-users were carried out in a vertically integrated structure. In time, the reform and deregulation process took place, and market activities were separated. In this context, reforms were made in electricity markets in many world regions, wholesale electricity markets were created, and generation, transmission, distribution, and supply activities were separated.

In Turkey, with Law No. 4628 in 2001, the Energy Market Regulatory Authority was established, and the separation of electricity market activities began with this law. Thus, electricity market activities excluding transmission were restructured, and a transition to a free market was made. In 2013, the new Electricity Market Law (EML) No. 6446 was enacted. With the new EML, the way for generation and supply activities to be carried out by licensed private companies has been paved, the feature of the Turkish Electricity Transmission Corporation (TEİAŞ) as the sole institution responsible for the transmission of electricity has been preserved, and distribution activity has been given the authority and responsibility of companies holding distribution licenses. With the new EML, the task of operating the wholesale electricity markets, excluding the markets served by Borsa İstanbul and TEİAŞ, was given to Energy Exchange Istanbul (EPİAŞ).

Today, the physical trade of electricity is carried out by bilateral agreements and additionally in Day-Ahead Market and Intraday Market, which EPİAŞ operates, and the Balancing Power Market operated by TEİAŞ. Furthermore, electricity trade with financial contracts is carried out in the Derivatives Market within Borsa İstanbul through electricity futures contracts (Devir, 2017).

Ziel et al. (2015) and Kristiansen (2014) state that the increase in liberalization in electricity markets contributes to the increase in the electricity trade volume through energy exchange and transparency in electricity prices and provides the advantage for market players to determine their positions by following price formations. In Turkey, as a result of liberalization in electricity markets, the volume of trade carried out through the energy exchange is increasing year by year. Table 1 shows this clearly.

Table 1. Distribution of Annual Electricity Market Amount Among Markets

YEAR	BILATERAL AGREEMENT	DAY-AHEAD MARKET (DAM)	INTRADAY MARKET (IDM)	BALANCİNG POWER MARKET (BPM)
2016	66%	27%	0.2%	7%
2017	67.7%	27.5%	0.4%	4.5%
2018	60.1%	37.1%	0.7%	2%
2019	56.6%	39%	1.4%	2.9%
2020	56.6%	40.2%	1.5%	1.6%

Source: EPİAŞ, 2016a; EPİAŞ, 2017; EPİAŞ, 2018; EPİAŞ, 2019; EPİAŞ, 2020.

According to Table 1, 66% of the total physical trade volume in the electricity market in 2016 was realized through bilateral agreements, 27% in DAM, 0.2% in IDM, and 7% in BPM. On the other hand, in 2020, 56.6% of the total physical trade volume was realized through bilateral agreements, 40.2% in DAM, 1.5% in IDM, and 1.6% in BPM. Although bilateral agreements are the most widely used way in physical electricity trade, the increasing share of the Day-Ahead Market in the total trade volume over the years reveals that DAM will become even more important in the coming period for market participants.

DAM, where electricity is traded one day before real-time, allows the market participants to balance the deficiencies or surpluses remaining from the bilateral agreements and leave a system to TEİAŞ that is balanced one day in advance (Yarıcı, 2018). In addition, the Market Clearing Price (MCP) is accepted as the reference price of electricity (Devir, 2017).

This study aims to forecast hourly MCP with deep learning techniques. In the literature, the importance of forecasting MCP for market participants has been emphasized by different authors. Huisman et al. (2007) and Raviv et al. (2015) point out that the prices formed in the DAM are the reference prices for market evaluations and financial contracts. Nogales et al. (2002) and Catalao et al. (2007) point out that forecasting MCP is important in maximizing producers' and suppliers' profits. Liu and Shi (2013) also state that forecasting electricity prices is important for developing bid and hedge strategies. According to Girish (2016), producers and suppliers can decide when it will be more profitable to sell and buy electricity by forecasting MCP. Besides, Tan et al. (2010) state that accurate price forecasting in the electricity market can enable producers and suppliers to adjust their bid strategies and develop risk management strategies with electricity derivatives to obtain maximum benefit. On the other hand, Amjady and Hemmati (2006) argue that with high-performance price forecasting, manufacturers can adjust their production schedules according to hourly MCP and their production costs, and suppliers can develop a bidding strategy that maximizes their benefit so that both parties can better negotiate bilateral agreements to gain an advantage at the point of price bargaining.

In DAM, market participants can submit price and quantity offers to buy and sell electrical energy with three different offer types: hourly bid, block bid, and flexible bid. These offers are given one day before the real-time for each hour of real-time. This study aims to develop a forecasting model to be a tool for market participants for developing a bid strategy and making production and supply planning. In this context, price forecasting for the next 24 hours has been carried out with deep learning techniques.

2. LITERATURE REVIEW

The liberalization of electricity markets and the transition to competitive electricity markets have made the forecasting of MCP a critical factor for all market participants. Producers and suppliers need MCP forecasting to determine the best bidding strategy and maximize their profits. In addition, MCP forecasting can play an essential role in the efficient functioning of the electricity market. This situation has increased the interest of researchers in MCP forecasting with various models and approaches in recent years. Statistical and artificial intelligence models are the leading methods commonly used in MCP forecasting (Yang et al., 2017). Univariate ARMA, ARIMA, Seasonal ARIMA (SARIMA) models, and models such as ARMAX, ARIMAX, and SARIMAX obtained by adding exogenous variables to these models, ARCH type models and various versions of these models were used in MCP forecasting. Among the statistical methods, studies based on MCP forecasting with the ARMA type models are the majority. Contreras et al. (2003), Weron and Misiorek (2006), and Cuaresma et al. (2004) forecasted electricity prices with ARMA-type models. On the other hand, Cervone et al. (2014) compared ARMA and GARCH models in forecasting electricity prices and found that the GARCH model performed better. However, according to Yang et al. (2017), artificial intelligence models have recently attracted the attention of many researchers in MCP forecasting.

Various forms of artificial intelligence models were used in electricity price forecasting in the literature. Keynia (2012) compared the ARIMA model with neural network (NN) and convolutional neural network (CNN) models in PJM, California, and Spain's electricity markets. Anbazhagan and Kumarappan (2014) forecasted prices of Spain and New York electricity markets using feed-forward neural networks. Chaabane (2014) forecasted Nordpool electricity market prices with ARFIMA and artificial neural network (ANN) models separately and in a hybrid model. Bento et al. (2018) used ARIMA, ANN, and CNN models to forecast PJM and Spain electricity market prices. Mirakyan et al. (2017) forecasted EPEX day-ahead electricity prices with ANN and Support Vector Machines models. Huang et al. (2020) used LSTM and CNN models to predict New York electricity market prices. Xie et al. (2018) forecasted PJM electricity market prices using CNN and LSTM methods separately and in a hybrid model. Similarly, Guo et al. (2020) also forecasted Liaoning electricity prices with the CNN-LSTM hybrid model, in which they included load and meteorological data. In another study using artificial intelligence models, Li and Becker (2021) forecasted Nord Pool electricity market prices with LSTM, CNN-LSTM, and ConvLSTM models.

In the literature, models such as ANN, CNN, LSTM, and hybrid models such as CNN-LSTM and ConvLSTM have been frequently used in electricity price forecasting. Chang et al. (2018) compared statistical models and artificial neural networks in electricity price forecasting and concluded that the performance of artificial neural networks is better than statistical models. According to Yang et al. (2017), artificial intelligence models can adjust the weights and capture the complex, dynamic and nonlinear features of electricity prices. Lago et al. (2018) state that innovations in artificial neural networks have increased in recent years, and methods are known as deep learning have given successful results in time series forecasting. In this context, Lago et al. (2018) compared 27 different statistical and artificial intelligence models and concluded that deep learning techniques outperform statistical methods in electricity price forecasting.

Considering the studies carried out in the Turkish electricity market, Özözen et al. (2016) created a hybrid model with the SARIMA and ANN models. They obtained a deviation of 10.2%, and with the ANN model Kölmek and Navruz (2015) obtained a deviation value of 14.15%. Uğurlu et al. (2018) obtained MAE values between 5.59 and 7.63 Euros with ANN, between 5.47 and 7.66 Euros with LSTM, and between 5,36 5,86 Euros with GRU. In another study, Gündüz et al. (2020) obtained an MAE value of 30.16 TL with LSTM, 30.04 TL with Encoder-Decoder LSTM, and 27.86 TL with Encoder-Decoder GRU in 24-hour forecasts.

In studies conducted in other markets, various MAPE values are obtained according to the market and forecasting period with various artificial intelligence models such as Backpropagation, ANN, MLP, CNN, RNN, LSTM, and GRU. Zhang et al. (2020a) obtained deviation values ranging from 5.87% to 16.83% in 24-hour price forecasts in the PJM electricity market with Backpropagation, CNN, and LSTM models, and Zhang et al. (2020b) obtained deviation values ranging from 5.77% to 18.80% in 1-hour price forecasts in Nord Pool market with MLP, GRU, and LSTM. In 24-hour forecasts for the PJM electricity market, Lyu et al. (2019) obtained deviations between 5.74%-9.05% with LSTM, and Hong et al. (2020) obtained deviations between 10.66%-16.63% with CNN. In the PJM electricity market, Khajeh et al. (2018) obtained deviation values between 4.41%-8.81% in 24-hour forecasts with RNN and between 6.77%-10.43% in 168-hour forecasts with MLP and CNN. In another 168-hour forecast, Aineto et al. (2019) obtained deviation values between 5.01%-24.22% with RNN in the Iberian market. In two separate studies applied in the EPEX market, Pao (2006) obtained MAPE values between 8.22-9.12 with ANN using daily prices, and Schnürch and Wagner (2020) obtained a MAPE value of 14.18 with feedforward neural network by using hourly prices. On the other hand, Lago et al. (2018) obtained sMAPE values between 13.04-13.91 with MLP, CNN, LSTM, and GRU in hourly price forecasting in the same market. In the New York electricity market, in 1-hour forecasts, Cheng et al. (2020) obtained MAPE values between 5.35-7.64 with Backpropagation, CNN, and LSTM, and Huang et al. (2020) obtained MAPE values between 5.23-6.55 with LSTM and CNN. In the Ontario market, Sahay (2015) obtained deviation values between 9.43%-41.97% in one-hour forecasts with ANN, and Jahangir et al. (2020) obtained deviation values between 8.31%-37.97% with CNN and LSTM.

Since artificial intelligence models can give different results in different markets, periods, and parameters, instead of making generalizations when comparing the forecasting results obtained with these models, inferences can be made about the performance of the models applied for a particular data set under certain parameters. Although this situation is not limited to artificial intelligence models, artificial intelligence models outperform statistical methods in modeling the complexity and nonlinearity of electricity prices (Weron, 2014).

3. DATA SET

This study forecasted the Market Clearing Price (MCP). While MCP was the dependent variable in the models, real-time consumption, load forecast plan, system marginal price (SMP), hydroelectric power plant production, temperature, wind speed, and day were included as exogenous variables.

The segmentation of the dataset for training, validation, and testing were as follows:

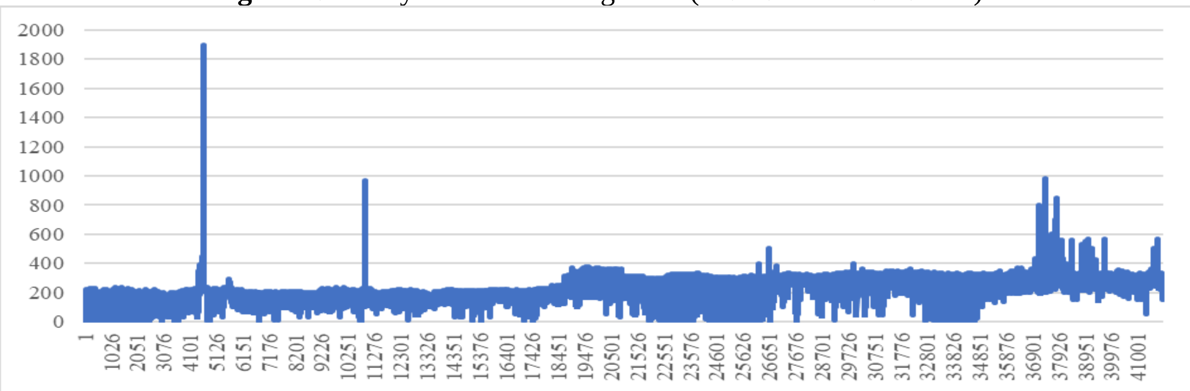
Training : 13.06.2016-04.10.2020

Validation : 05.10.2020-28.02.2021

Test : 01.03.2021-28.03.2021

EPİAŞ determines MCP by using optimization software for every day of the week and all 24 hours. This software evaluates the price and quantity offered by market participants to buy and sell in DAM for 24 hours by using heuristic algorithms and a mathematical program solver. It determines the matching quantity and price (EPİAŞ, 2016b). Figure 1 shows hourly MCP for the period 13.06.2016-28.03.2021.

Figure 1. Hourly Market Clearing Price (13.06.2016-28.03.2021)



Source: EPİAŞ Transparency Platform.

In the figure, the 'x' axis shows the hours, and the 'y' axis shows price as TL/MWh. The Day-Ahead Market Clearing Price can be 0, but there have also been time zones between 600 TL/MWh and 1,800 TL/MWh by showing jumps. In this period, the average MCP was 228.08 TL/MWh, and it exhibited a volatile structure above and below this value. Chaabane (2014) states that electricity prices are subject to day and week effects, jumps, and level changes, which can be explained by seasonal fluctuations in electricity demand and production.

In the analysis, exogenous variables were selected based on the literature. Li et al. (2005) state that past prices and consumption are related to future prices and consumption while matching amount is related to past consumption. They also state that generation cost depends on fuel prices, hydroelectric generation may affect MCP, and temperature is a criterion for measuring weather change. In this study, days of the week, past consumption values, load forecast plan, system marginal price, hydroelectric generation amount, temperature, and wind speed were exogenous variables. Table 2 summarizes the exogenous variables.

Table 2. Exogenous Variables

VARIABLE CODE	VARIABLE DESCRIPTION	PERIOD
DAY	Days of the Week and Public Holidays	MCP Period
RTC	Real Time Consumption	MCP Period - 24 Hour
HPP	Real-Time Hydroelectric Power Plant Production Amount	MCP Period - 24 Hour
TEM	Temperature	MCP Period
WIS	Wind Speed	MCP Period
SMP	System Marginal Price	MCP Period - 24 Hour
LFP	Load Forecast Plan	MCP Period

The periods of the exogenous variables were determined according to the characteristics of each variable. The DAY variable can be created for the same period as MCP. For the DAY variable, the days of the week were coded as 1-2-3-4-5-6-7, respectively, starting from Monday and ending on Sunday. In the period under consideration, the days leading to public holidays were coded as 8. This coding was made to be the same at every hour of the same day. For the RTC, HPP, and SMP variables, the values realized 24 hours before the MCP period were taken. On the other hand, LFP can be obtained in the same period as MCP. RTC, HPP, SMP, and LFP were obtained from the EPİAŞ Transparency Platform. HPP consists of the amount of hydroelectric energy produced by both dams and streams.

While creating TEM and WIS data, the provinces with dense solar and wind power plants were selected. For this, the total installed power amounts of both solar and wind power plants based on provinces were determined using the Enerji Atlasi web page data as of 01.04.2021. The provinces were ranked for both types of plants based on the total installed power. The data for the first eight provinces were obtained from the General Directorate of Meteorology. The first eight provinces determined for the temperature variable were Konya, Kayseri, Ankara, Niğde, Afyonkarahisar, Gaziantep, Antalya and Denizli, respectively. The total solar power plant installed power in these provinces represented 71% of Turkey's total solar power plant installed capacity. The first eight provinces determined for the wind speed variable were İzmir, Balıkesir, Manisa, Çanakkale, Hatay, Afyonkarahisar, İstanbul and Aydın, respectively. The total wind power plant installed power in these provinces represented 63% of Turkey's total wind power plant installed capacity. The temperature was obtained in °C, and wind speed was obtained in meters/second. In the case of temperature and wind speed data gaps, these gaps were filled by averaging the previous and next hour data.

4. METHODOLOGY

In this study, MCP was forecasted by deep learning techniques. These techniques are stated by Yang et al. (2017) as having the ability to adjust the weights and thus capture the complex, dynamic and nonlinear features of electricity prices. Lago et al. (2018) also state that they give more successful results than statistical methods in time series forecasting. In this study, MCP was forecasted using MLP, CNN, LSTM, and GRU models.

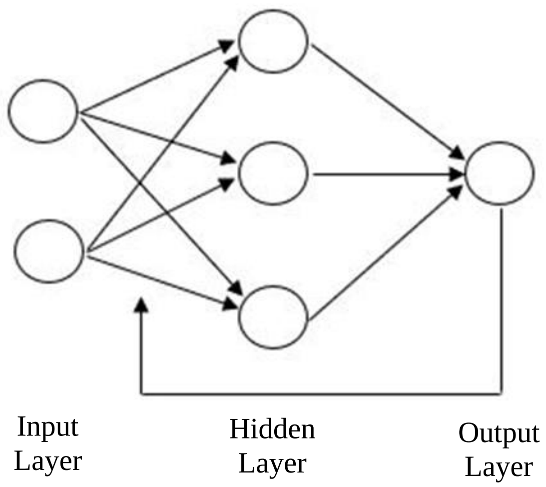
In the first stage, the models were trained with the data for the period 13.06.2016-04.10.2020. In the second stage, the models were validated by forecasting MCP for 3,528 hours by going 1 step forward in each cycle on the data for the period 05.10.2020-28.02.2021. Finally, the models were trained with the data for the period 13.06.2016-28.02.2021, and 24-hour MCP for the period 01.03.2021-28.03.2021 was forecasted by adding the next 24-hour data to the training data in each cycle.

4.1. Multilayer Perceptrons (MLP)

Artificial neural networks are artificial intelligence methods that try to learn by imitating the information acquisition and processing of the human brain. The most widely used artificial neural network method is the perceptual network model with multiple layers, called multilayer perceptrons (Mirakyan et al., 2017). Artificial neural networks consist of several interconnected nodes known as neurons. These nodes are used to perform nonlinear transformations on the original input features. A multilayer neural network includes at least one hidden layer, apart from the input and output layers. (Lewis, 2017). Neural network models with one or more hidden layers are called as deep learning (O'Shea and Nash, 2015). The neurons in the hidden layers provide a relationship between the input and the output. In cases where the size of the input layer is large, the hidden neurons play an important role in obtaining high-order statistics (Gupta and Sinha, 2000).

Figure 2 shows an example of the backpropagation multilayer perceptron model with a single hidden layer. While training the network, a supervised learning technique called backpropagation is used, in which the error between the forecasted and the actual is calculated (Hassim and Ghazali, 2012).

Figure 2. Backpropagation Multilayer Perceptron with A Single Hidden Layer



Source: Anochi and Velho (2016).

The estimated value in the multilayer perceptron model is calculated with formula 1 (Mirakyan et al., 2017):

$$f(x) = \sum_{n=1}^{n_h} W_{jh}\sigma(X)\,(\textstyle\sum_{i=1}^{n_i} W_{ih}X_i + W_{0h}) + W_{0j} \qquad (1)$$

In formula 1, n_i and n_h are the numbers of neurons in the input and hidden layers. X_i is the input, and W_{jh} is the weight between the hidden and the output layers. W_{ih} is the weight between the input layer and the hidden layers. W_{0h} is the weight between the fixed input and the hidden layers. W_{0j} is the weight between fixed input and the output layer, and σ is the activation function. In the backpropagation model, the variables are presented to the network, initial weights assigned to each neuron are multiplied by the values of the variables, and the obtained values are summed. The bias value is added to the sum and sent to neurons in other layers with the activation function. These values are the input values of that layer. In this way, errors are calculated by comparing the outputs produced by the network in the last output layer with the actual data (Mirakyan et al., 2017; Ser and Bati, 2019).

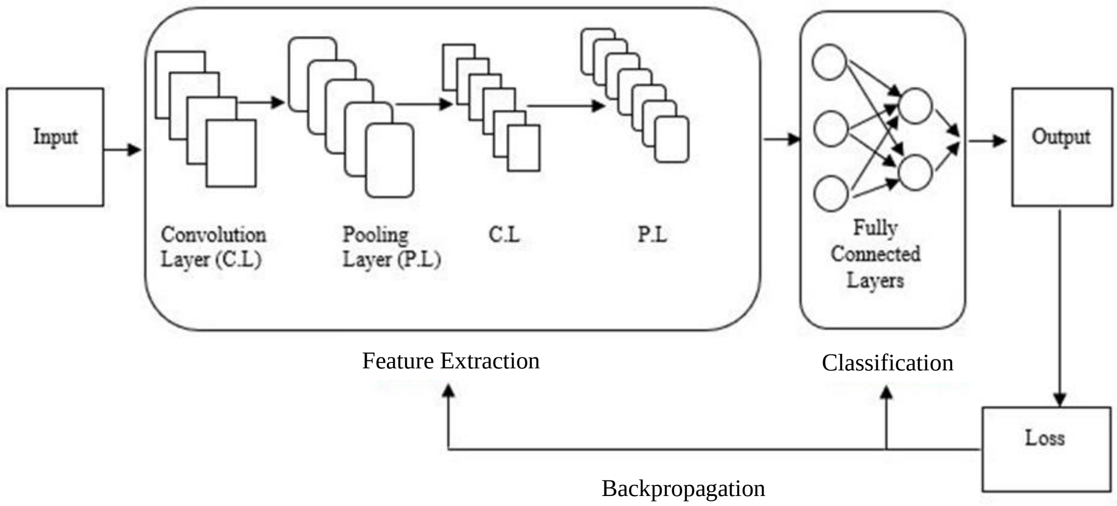
$$W_{ji} = W_{ij}(t-1) + \Delta W_{ji}(t) \qquad (2)$$

In the backpropagation stage, the weights indicated by W_{ji} in formula 2 are updated according to the time 't-1' in the 't' iteration. $\Delta W_{ji}(t)$ in the formula expresses the change in weights (Mirakyan et al. 2017).

4.2. Convolutional Neural Networks (CNN)

CNN uses a special linear mathematical operation, called convolution, in at least one of its layers to process data (Goodfellow et al., 2016). Convolutional neural networks consist of neurons that self-optimize through learning. Each neuron performs a process with the inputs, as in artificial neural networks. A loss function is obtained by comparing the forecasted output with the actual in the last layer. The same process for artificial neural networks is also valid for convolutional neural networks. However, unlike artificial neural networks, convolutional neural networks use a pattern recognition area to recognize the inputs in the first stage (O'Shea and Nash, 2015). In particular, compared to standard neural networks with similarly sized layers, they can be trained more smoothly because they have fewer connections and parameters (Krizhevsky et al., 2017). The convolutional neural network structure is shown in Figure 3.

Figure 3. Convolutional Neural Network Structure



Source: Kim (2017); Yamashita et al. (2018); Indolia et al. (2018).

The CNN model is implemented with the following formulas (Indolia et al., 2018):

$$C_q^l = (\sum_{p=1}^{n} \sum_{u=-x}^{x} \sum_{v=-x}^{x} S_p^{l-1}(i-u, j-v) \left(k_{p.q}^l(u,v)\right)) + b_q^l \quad (3)$$

$$S_q^l(i,j) = \frac{1}{4} \sum_{u=0}^{z} \sum_{v=0}^{z} C_q^l(2i-u, 2j-v) \quad (4)$$

$$output = \sigma(W * f + b) \quad (5)$$

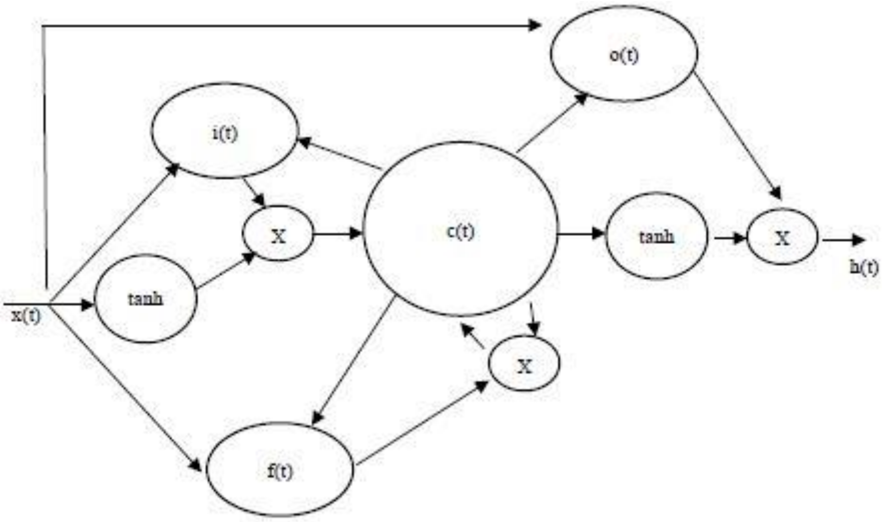
$$y(i) = \frac{e^{output}}{\sum_1^{labels} e^{output}} \quad (6)$$

In formula 3, n is the number of feature maps in the last layer, p is the feature map indexes of the current layer, and q is the feature map indices of the previous layer. L is the layer, b, and x, respectively, the offset and size of the filter. S_p^0 and S_p^1 are the inputs on which convolution will be performed. After the convolution, the pooling layer is applied using formula 4. In Formula 4, z is the pool window size. In formula 5, f represents the final output, W represents the weight vector of the fully connected layer, and σ is the activation function. Labels in Formula 6 represent the number of class labels. After the convolution and pooling process, the information is passed through the fully connected layer using formula 5, and classification is made with formula 6 (Indolia et al., 2018).

4.3. Long Short Term Memory (LSTM)

Recurrent neural network is a type of neural network with loops that allow the permanent use of information from the past in the network structure (Shewalkar, 2018). In RNN, the gradient of the weights becomes too small or too large as the time step gets longer. If the gradients are too large, there is a gradient explosion, and when the gradients become too small to spread, gradient disappearance is encountered (Kumar et al., 2018). LSTM and GRU models, variations of recurrent neural networks, were developed to solve the gradient disappearance problem encountered in RNN (Althelaya et al., 2018). LSTM, a special type of repetitive neural network with memory cells, remembers information for a long time with the help of memory cells (Shewalkar, 2018:). Figure 4 shows the memory block in the LSTM model.

Figure 4. LSTM Memory Block



Source: Lewis (2017).

In the figure, x(t) represents the values entering the memory block. C(t) represents the memory cell, i(t) represents the input gate, f(t) represents the forget gate, o(t) represents the output gate. Tanh is the activation function, and h(t) represents the values leaving the memory block. There is a memory cell and there are three multiplicative gate units in the memory block. These gates regulate the information entering and leaving the memory cell (Lewis, 2017). The input gate performs the function of receiving and processing new information from the outside, the forget gate performs the function of deciding when to forget the output results. The output gate performs the function of producing output for the LSTM cell by taking all the calculated results (Fu et al., 2016).

The operation of the LSTM memory block is carried out by following the mathematical flow in formula 7, formula 8, formula 9, formula 10, formula 11, and formula 12 (Kumar et al., 2018):

$$f_t = \sigma(W_f * (h_{t-1}, x_t) + b_f \quad \text{‘}\sigma = \text{aktivaston fonksiyonu’} \tag{7}$$

$$i_t = \sigma(W_i * (h_{t-1}, x_t) + b_i \tag{8}$$

$$C'_t = \tanh(W_c * (h_{t-1}, x_t) + b_c) \tag{9}$$

$$C_t = f_t * C_{t-1} + i_t * C'_t \tag{10}$$

$$O_t = \sigma(W_o * (h_{t-1}, x_t) + b_0 \tag{11}$$

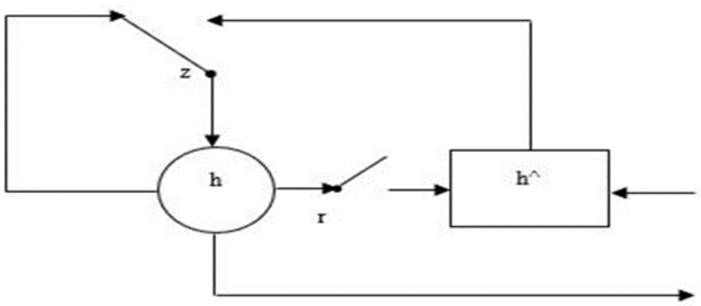
$$h_t = O_t * \tanh(C_t) \tag{12}$$

Looking at h_{t-1} and x_t, it is decided which information should be discarded using an activation function. A number between 0 and 1 is assigned for each information. 1 represents information hiding, and 0 represents getting rid of information. In order to decide which new information coming into the cell should be stored, the entrance gate first decides which values need to be updated. Next, C_t (vector of new values) is created via the tanh activation function. In the last stage, the values in the cell memory are combined with the new values (Kumar et al., 2018).

4.4. Gated Recurrent Unit (GRU)

Like LSTM, the GRU model is designed to remember data from the previous time step. While LSTM uses three gates, the GRU uses two gates as the reset gate and update gate. The reset gate is used to decide how much of the past information should be forgotten or remembered. The update gate determines how much of the information from the previous time steps should be transferred to the future (Khan and Sarfaraz, 2019). The network structure of the GRU consists of blocks of gated recurrent units for memory reset and updating control. GRU, which uses fewer parameters than the LSTM model, performs faster learning processes (Althelaya et al., 2018).

Figure 5. GRU Memory Block



Source: Chung et al. (2014).

Figure 5 shows the memory block of the GRU model. The r node in the block represents the reset gate, and the z node represents the update gate. The h and h^ layers in the block represent the activation functions (Chung et al., 2014). In the GRU block, the information flow is carried out in the hidden layers of the block rather than in a separate memory cell. The reset gate, which can transmit and block information from the previous time step to the model, resets the information when it is no longer relevant. The update gate helps catch long-term dependencies. If it is decided that the memory content is important, the update gate is closed, and the memory content is moved in multiple time steps. The last memory content consists of a weighted combination of the new and previous memory content (Lewis, 2017).

The operation of the GRU memory block is carried out by following the mathematical flow in formula 13, formula 14, formula 15, and formula 16 (Shen et al., 2018):

$$u_t = s(W_u[h_{t-1}, x_t]) \quad (13)$$

$$r_t = s(W_r[h_{t-1}, x_t]) \quad (14)$$

$$h_t^{\wedge} = \tanh\,(W[r_t * \ h_{t-1}, x_t]) \quad (15)$$

$$h_t = (1-u) * h_{t-1} + u_t * \hat{h_t} \quad (16)$$

Formula 13 is the mathematical representation of the reset gate. The reset gate is used to control the effect of the previous time step, h_{t-1}, on the current information indicated by x_t. If h_{t-1} is not important to x_t, the r_t gate is opened so that h_{t-1} does not affect x_t. Formula 14 is the mathematical representation of the update gate. A short-circuit connection from h_{t-1} to h_t occurs when the update gate is opened, and x_t is ignored. Formulas 15 and 16 are mathematical representations of the output obtained in the GRU model. According to the formulas mentioned above, GRU networks process the inputs at each t-step and return the final output. Network training is completed by adjusting the parameters to minimize the loss function (Shen et al., 2018).

4.4. Hyperparameters and Evaluation Criteria

In the models, the past 24 values of the variables were used as inputs to forecast 24 steps (hours). One hundred nodes, 20 epochs, and 20 batches were used in all models. In the CNN model, five parallel filters and 64 kernels were used. All models used 'relu' as activation function, 'adam' as optimization algorithm, and 'mse' as loss function. Analyzes were performed by using the Python 3.7 programming language. Five hidden layers were used in the models, and the 'dropout' technique was applied between the layers to prevent overfitting.

In the study, MAPE value, which is one of the metrics commonly used in the literature, was used to measure model performance. MAPE (mean absolute percentage error) is represented by formula 17 (Kouhi and Keynia, 2013):

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\frac{|L_{realized}(k) - L_{forecasted}(k)|}{L_{realized}(k)} \quad (17)$$

In formula 17, N shows the forecasted number of steps, $L_{realized}(k)$ shows realized price in k hours and $L_{forecasted}(k)$ shows forecasted price in k hours (Kouhi and Keynia, 2013).

5. FINDINGS

5.1. Models Performances for Validation

All models were trained with the data for the period 13.06.2016-04.10.2020. Then, hourly MCP for 05.10.2020-28.02.2021 was forecasted for validation. Each of the models was run three times for validation, and the model performances were evaluated by taking the average of the results obtained. The performance of the models in each run is given in Table 3.

Table 3. Model Performances for Validation

VALIDATION	MLP	CNN	LSTM	GRU
First Run	7.54	9.26	8.65	8.98
Second Run	9.06	7.59	8.74	9.16
Third Run	8.72	7.43	8.99	6.79
AVERAGE MAPE	**8.44**	**8.09**	**8.79**	**8.31**

In the analyzes performed for the validation, CNN showed the best performance with an average MAPE value of 8.09, while GRU with an average MAPE value of 8.31, MLP with an average MAPE value of 8.44 and LSTM with an average MAPE value of 8.79.

5.2. Models Performances for Test Period

After validation, 24-hour MCP for the period 01.03.2021-28.03.2021 was forecasted. The average MAPE values obtained for every 24 hours of the 28 days test period with the MLP, CNN, LSTM, and GRU models are shown in Table 4.

Table 4. Model Performances for Test Period

TEST PERIOD	MLP	CNN	LSTM	GRU
01.03.2021	7.72	7.11	14.75	13.89
02.03.2021	4.20	10.46	6.88	6.09
03.03.2021	5.04	7.58	5.77	4.35
04.03.2021	9.40	9.56	3.15	6.53
05.03.2021	7.88	4.75	5.73	4.93
06.03.2021	7.22	8.36	7.12	7.62
07.03.2021	10.96	13.48	10.37	11.24
08.03.2021	8.74	9.91	6.96	12.53
09.03.2021	4.00	5.89	4.13	4.15
10.03.2021	6.66	8.15	2.38	6.69
11.03.2021	6.05	4.05	3.87	4.58
12.03.2021	10.10	12.51	5.83	9.09
13.03.2021	6.14	4.35	7.84	4.97
14.03.2021	6.85	8.26	5.79	6.93
15.03.2021	6.82	6.40	6.27	9.28
16.03.2021	4.78	6.37	8.93	6.02
17.03.2021	9.32	10.80	5.58	8.02
18.03.2021	7.01	9.61	7.38	5.82
19.03.2021	16.01	16.38	8.63	15.33
20.03.2021	11.07	14.31	16.68	10.99
21.03.2021	9.64	5.90	14.45	9.64
22.03.2021	6.91	8.46	9.88	10.42
23.03.2021	8.89	10.38	9.81	8.37
24.03.2021	10.95	16.18	8.47	11.83
25.03.2021	5.71	7.62	7.20	5.16
26.03.2021	10.94	11.38	6.84	9.84

27.03.2021	12.30	9.40	8.01	11.25
28.03.2021	15.09	12.00	19.40	18.61
AVERAGE MAPE	**8.44**	**9.27**	**8.15**	**8.72**

According to Table 4, the model with the best performance was the LSTM, with an average MAPE value of 8.15. The LSTM was followed by MLP with an average of 8.44 MAPE value, GRU with an average of 8.72 MAPE value, and CNN with an average of 9.72 MAPE value, respectively.

According to the results obtained, the best prediction performance of the MLP had a 4.00 MAPE value, and the worst had a 16.01 MAPE value. The best prediction performance of the CNN had a 4.05 MAPE value, and the worst had a 16.38 MAPE value. The best prediction performance of the LSTM had a 2.38 MAPE value, and the worst had a 19.40 MAPE value. The best prediction performance of the GRU had a 4.15 MAPE value, and the worst had an 18.61 MAPE value.

Figure 6. Distribution of Test Period 24-Hour Forecast Results

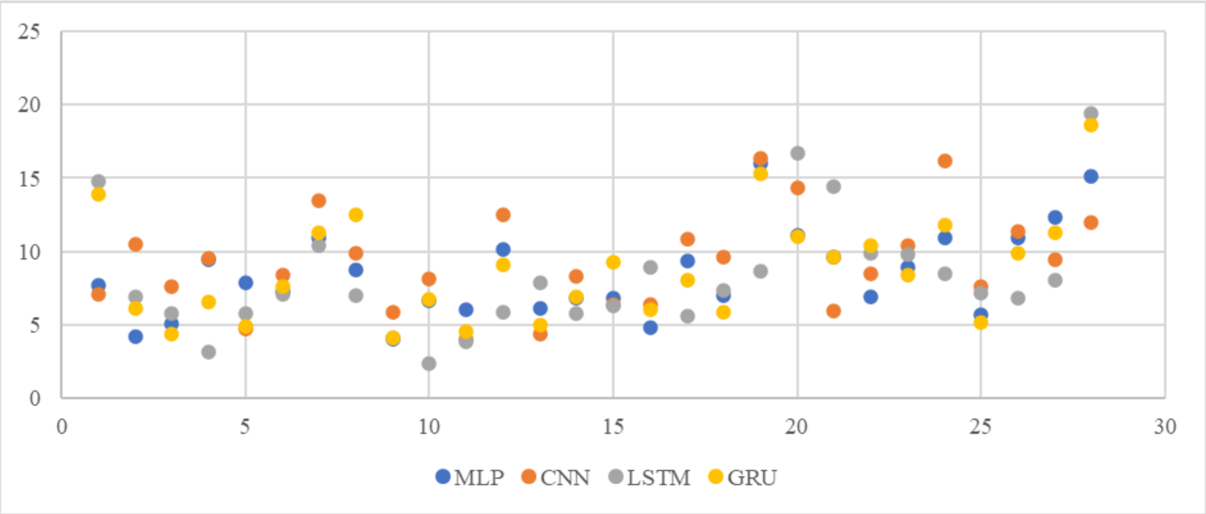


Figure 6 shows the distribution of the MAPE values of the 24-hour forecast results obtained with the MLP, CNN, LSTM, and GRU models during the test period. In the distribution of MAPE values of MLP, the forecasts for three days had a deviation below 5%, seventeen days between 5% and 10%, six days between 10% and 15%, and two days above 15%.

In the distribution of MAPE values of CNN, the forecasts for three days had a deviation below 5%, fifteen days between 5% and 10%, eight days between 10% and 15%, and two days above 15%.

In the distribution of MAPE values of LSTM, the forecasts for four days had a deviation below 5%, nineteen days between 5% and 10%, three days between 10% and 15%, and two days above 15%.

In the distribution of MAPE values of the forecast results of GRU, the forecasts for five days had a deviation below 5%, fourteen days between 5% and 10%, seven days between 10% and 15%, and two days above 15%.

Figure 7. MLP Model Test Period 24-Hour Forecast Results

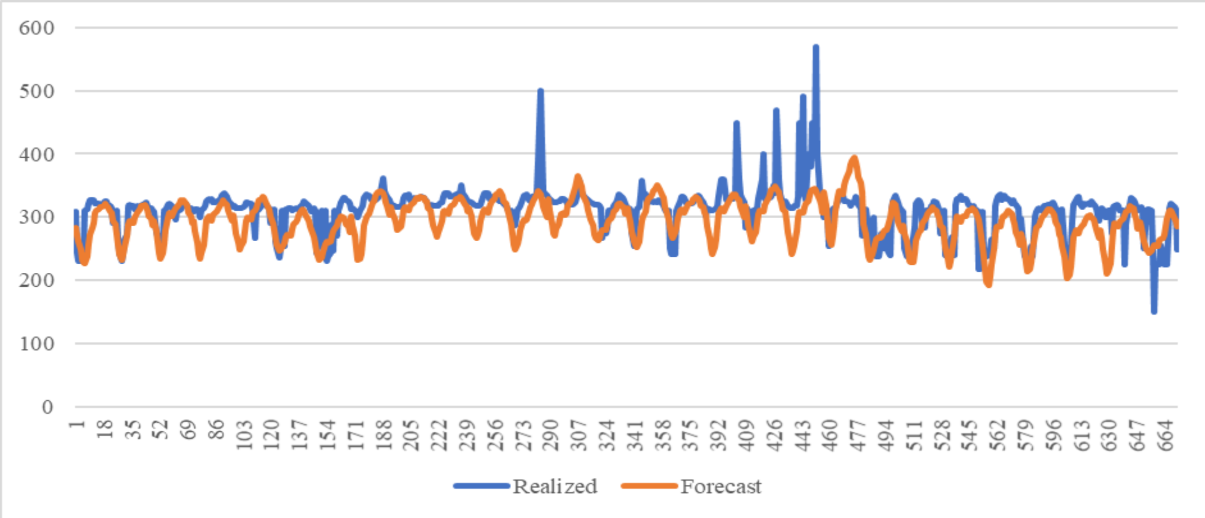


Figure 7 shows MLP's performance in catching the realized MCP for 28 days, covering 01.03.2021-28.03.2021. In Figures 7, 8, 9, and 10, the 'x' axis shows the hours, and the 'y' axis shows the price as TL/MWh.

Figure 8. CNN Model Test Period 24-Hour Forecast Results

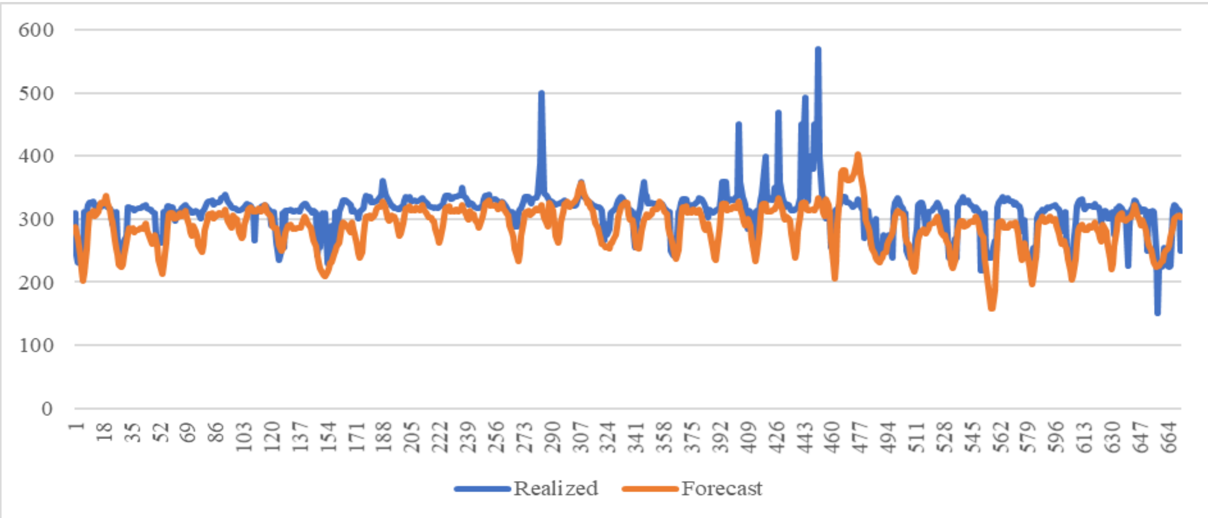


Figure 8 shows CNN's performance in catching the realized MCP for 28 days, covering 01.03.2021-28.03.2021.

Figure 9. LSTM Model Test Period 24-Hour Forecast Results

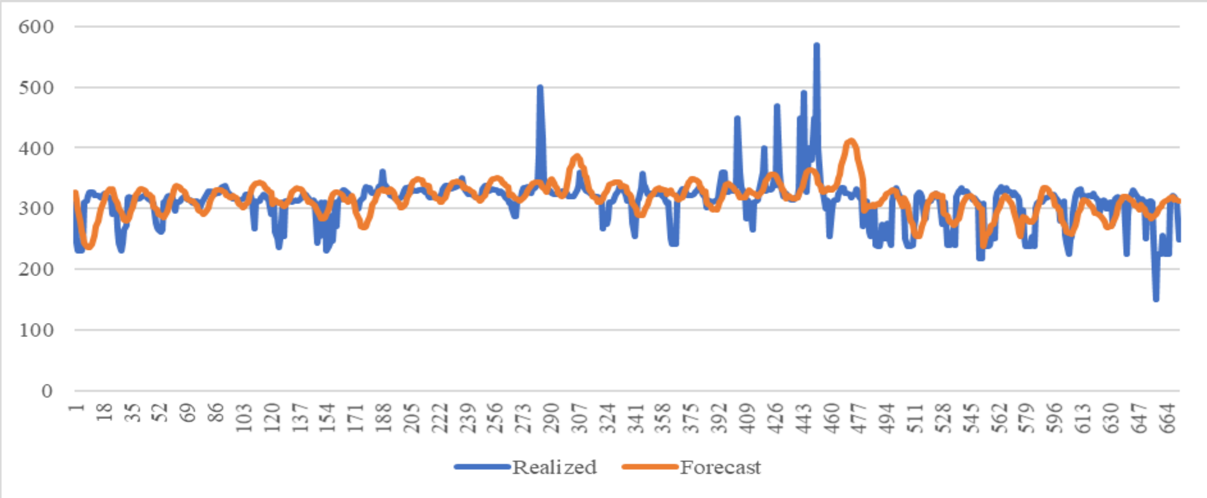


Figure 9 shows LSTM's performance in catching the realized MCP for 28 days, covering 01.03.2021-28.03.2021.

Figure 10. GRU Model Test Period 24-Hour Forecast Results

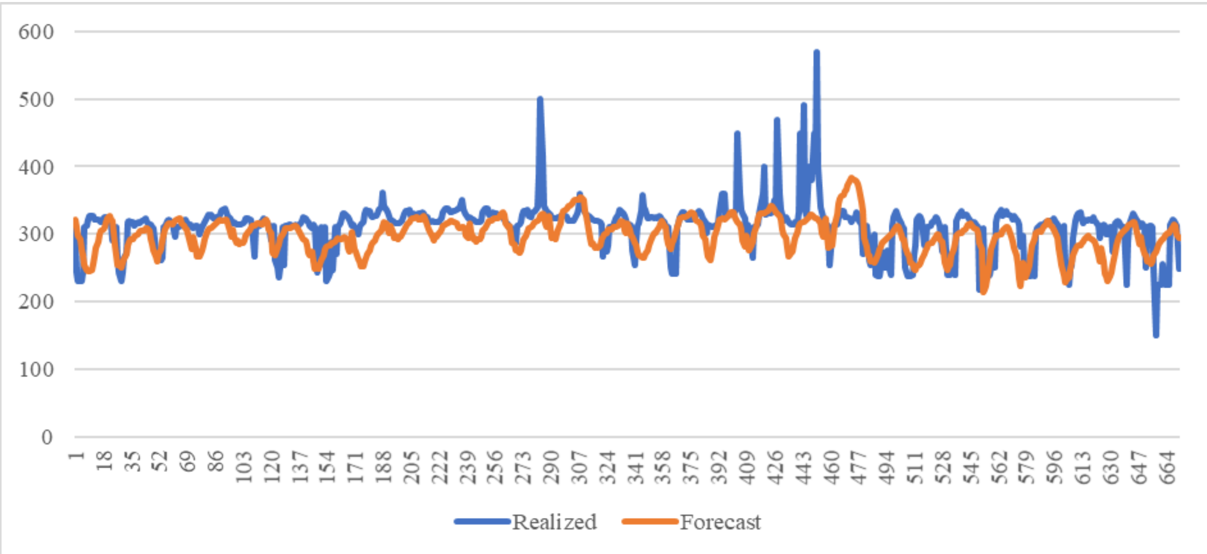


Figure 10 shows GRU's performance in catching the realized MCP for 28 days, covering 01.03.2021-28.03.2021.

Table 5. Test Period MAPE Values Based on Days

DAYS	MLP	CNN	LSTM	GRU
Monday	7.55	7.97	9.46	11.53
Tuesday	5.47	8.28	7.44	6.16
Wednesday	7.99	10.68	5.55	7.72
Thursday	7.04	7.71	5.40	5.52
Friday	11.23	11.26	6.76	9.80
Saturday	9.18	9.10	9.91	8.71
Sunday	10.64	9.91	12.50	11.60

Table 5 shows the average MAPE values of the forecasting results obtained during the test period based on each day of the week. Accordingly, the best average forecast performance of the MLP was on Tuesday, the best average forecast performance of the CNN, LSTM, and GRU was on Thursday.

Table 6. Test Period MAPE Values Based on Hours

HOURS	MLP	CNN	LSTM	GRU
00-01	5.83	7.14	4.37	7.29
01-02	8.35	8.38	5.66	10.63
02-03	10.04	7.65	9.20	10.45
03-04	10.31	8.30	12.23	8.80
04-05	13.07	12.21	11.67	10.49
05-06	13.91	17.35	8.56	9.59
06-07	15.89	19.63	5.45	8.71
07-08	10.69	11.32	8.21	10.03
08-09	10.31	10.88	9.57	8.89
09-10	12.81	9.29	14.90	13.74
10-11	10.32	7.55	10.19	10.45
11-12	10.86	7.96	10.13	10.94
12-13	5.30	6.43	7.98	6.62
13-14	5.18	6.37	9.55	6.69
14-15	4.97	7.73	7.66	6.44
15-16	6.31	7.64	10.32	8.09
16-17	5.66	7.16	8.50	6.87
17-18	5.24	8.48	6.72	7.01
18-19	4.06	7.13	4.75	6.33
19-20	8.37	9.97	7.81	10.34
20-21	5.57	8.17	5.37	6.88
21-22	5.18	7.69	3.95	5.75
22-23	6.60	8.95	5.23	8.70
23-24	7.81	9.16	7.53	9.53

Table 6 shows the average MAPE values of the forecasting results obtained during the test period based on each hour of the day. Accordingly, the best average forecast performance of the MLP was between 18-19 hours, the best average forecast performance of the CNN was between 13-14 hours, and the best average forecast performance of the LSTM and GRU was between 21-22 hours.

6. CONCLUSION

This study aims to develop a forecasting model for MCP to be a tool for bidding strategy in DAM, and planning production and supply programs. In this direction, MLP, CNN, LSTM, and GRU models were used to forecast the next 24-hour MCP. The results show that the models used gave very close results to each other. Lewis (1982, as cited in Klimberg et al., 2010) states that forecasts with less than 10% deviation are highly accurate, forecasts deviating between 11% and 20% are good, forecasts deviating between 21% and 50% are reasonable, and forecasts deviating from 51% or more are inaccurate. In this context, it can be said that the average forecasting results in this study with deviations in the range of 8.15%-9.27% obtained by the models are highly accurate forecasts.

On the other hand, the distribution of the deviation values is important in evaluating the performance of the models. In this study, MLP's performance was between 4.00-16.01, the CNN's performance was between 4.05-16.38, the LSTM's performance was between 2.38-19.40, and the GRU's performance was between 4.15-18.61 MAPE. The LSTM model, which had a deviation of less than 10% in the 23 days forecast results, shows the best performance in the distribution of forecast results. In general distribution, out of 112 forecasts made with four different models for the 28-day test period, 15 of them were below 5% deviation, 65 of them were between 5%-10% deviation, 24 of them were between 10%-15% deviation, and 8 of them were between 15%-20% deviation. It can be said that the majority of them are highly accurate forecasts and the remaining ones are within the limits of good forecasts.

For generation companies, the cost of the electricity produced and in which market, and at what price the energy will be sold are crucial. For the supply companies, the sales price in the contracts and the electricity price that will be purchased are critical factors that affect the profit. In this context, accurate price forecasting is an essential tool for market participants, both in hourly generation and supply planning and in using various electricity markets and bid strategies more effectively. While developing bid strategies, evaluating the results based on days of the week and hours of the days, as in this study, can benefit market participants in maximizing profits.

In this study, the data of the stations in the provinces where the total installed capacity of solar and wind power plants is the highest were used. In Turkey, electricity generation with renewable energy resources is encouraged. According to TEİAŞ electricity statistics, the share of electricity generation plants based on renewable energy resources in the total installed power is increasing. Electricity generation with renewable resources fluctuates depending on time and region, and generation with renewable resources can significantly reduce electricity production costs. For this reason, it is thought that the market participants in MCP forecasting should consider the factors that may affect the electricity production of renewable resources.

For future studies, the inclusion of the Power Futures Market data, which has just started operating within EPİAŞ, into the models, forecasting by hybrid deep learning models, and forecasting by creating separate time series for each hour is recommended.

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