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Forecasting the day-ahead price in electricity balancing and settlement market of Turkey by using artificial neural networks

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Abstract: In determination of electric energy price, most price information coming from bilateral contracts is effective, but the importance of the spot market (pool market) price cannot be ignored. Forecasting the spot market price is very crucial, especially for companies actively participating in the spot market and giving purchase and sale bids. An artificial neural network is a way frequently used for price forecasting research. In this study, simulation studies about price modeling via artificial neural networks and proper artificial neural network configurations are examined. After selection of different network topologies and parameters, attempts are made to observe network performance by error rates and find the best suitable configuration. Moreover, a time series model is made and it is compared with the artificial neural network's error performance.

Key words: Artificial neural networks, Turkish electricity market, day-ahead price, time series

1. Introduction

Before the early 1990s, there was a unique electricity company called the Turkish Electricity Company (Turkish acronym: TEK), and all generation, transmission, and distribution works were conducted by TEK. During the liberalization and privatization process of the Turkish electricity market, the vertically integrated company TEK was separated into four different companies as the Turkish Electricity Transmission Company (TEİAŞ), Turkish Electricity Distribution Company (TEDAŞ), Electricity Generation Company (EÜAŞ), and Turkish Wholesale Company (TETAŞ). When the electricity market law was enacted in 2001, an independent market regulator, the Energy Market Regulatory Authority (EPDK) was founded with the mission of liberalizing the electricity market, controlling market players, and regulating market rules.

Electricity trading was governmentally controlled when the state-owned company TEK was active. The liberalization process brought a liberal market where participants of the electricity market could sell/buy electricity in a market environment. In addition to the derivative companies of TEK listed above, private-sector companies (they could be generation, distribution, and wholesale company or auto-producers), generators having special privileges (build-operate-transfer, etc.), and consumers could be counted as market participants. The electricity trade has two major instruments: bilateral contracts and the spot (pool) market.

One of novelties that the liberalized environment brings is determination of electricity energy prices under market conditions and within economic models. Nowadays, the price of electricity is settled by both bilateral contracts and spot market price. Mostly bilateral contracts affect the price of electricity; however, spot market

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price also has a crucial impact on the determination of the price. Therefore, forecasting the spot market price is very important for firms that participate in the spot market actively and give buy/sell offers.

Spot market prices settled in electricity markets generally have high frequency and volatility. Those prices do not have a constant mean and variance, and they have high sudden peaks and sharp falls. Prices are shaped by daily and seasonal codes, and weekends and holidays affect price tops and bottoms [1].

Those properties of prices can be seen in Figure 1, showing the day-ahead price distribution of 2010 for Turkey. As can be deduced from the graph, throughout the price distribution, there are not only sudden jumps, but there is also daily and weekly seasonality.

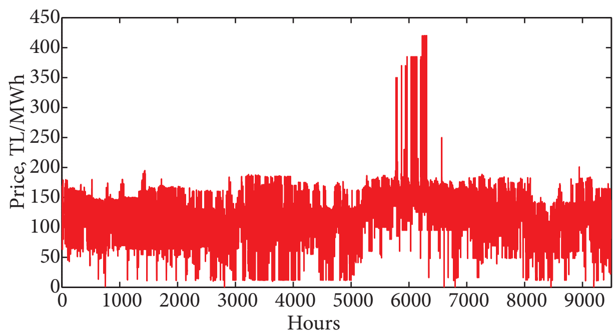

Figure 1. The day ahead price distribution of 2010 (TL: Turkish lira).

Hamzaçebi divided estimation methods of data whose behavior has such a variable and different structure into two, as quantitative and qualitative methods depending on the data set and data process [2]. Quantitative estimation methods are divided into two as methods based on 'cause-effect relations' and 'time-series analyses'.

According to Niimura [3], two main methods are commonly used for price estimation. These are the simulation method and time-series analysis, similar to the differentiation above. The simulation method generally includes 'cost-based' optimization. Time-series analysis is basically divided into three categories. These are linear regression, stochastic modeling, and the nonlinear heuristic model. Stochastic models normally have been developed for the stock market. Those models, which still use time-series data, are used for position detection rather than price estimation. While autoregression (AR), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA) models target price estimation depending on data with past dates, regression models like generalized autoregressive conditional heteroskedasticity target the estimation of fluctuations in price. Fuzzy methods, chaotic models, evolutionary calculations, and artificial neural networks (ANNs) are some of the nonlinear heuristic models. While these models are used alone sometimes, a mixed modeling method is implemented in some studies.

In the literature, it is seen that time-series analysis of price estimation by dynamic regression, AR, ARMA, and ARIMA models is important [4–12]. Furthermore, studies on models built via wavelet transform [13–16], estimation via transfer function [17], and hybrid models developed as mixed methods [18,19] have been done.

Another commonly used tool for estimation of electricity prices is ANNs. The reason to prefer ANNs is that they have the ability to learn difficult and complex relations that are difficult to model with conventional methods [20]. Although it is said that ANNs are intended to establish a relation between inputs and outputs without dealing with the mechanism behind related process, they can be also used as a significant tool for detection of structural relations in terms of showing weights of given inputs on outputs.

Regarding the electricity market, early studies on estimation of demand or estimation of load [e.g., 21–

23] were a starting point for the price estimation model. In these models, past data about load as well as temperature, available capacity, and codes of days were used.

The pioneer study on price estimation in the electricity market performed via ANNs was that of Wang and Ramsay in 1997 in order to estimate "system marginal price" recognized in United Kingdom's energy pool market [24]. The modeling was realized for each settlement period. Settlement periods were differentiated into two groups, as the case where planned production capacity for the period is more than the demand that should be met in that period at certain levels and all other cases. In this study, a feedforward backpropagation multilayer ANN having 12 input neurons is used. The inputs and outputs of the system are illustrated in Table 1.

Table 1. Input Set of Wang and Ramsay [24].

	Definition	Symbolic representation
Inputs	Code for the day to forecast (weekend, holiday, etc.)	D(i)
	Settlement period index	T(i,t)
	Load amount to forecast	L(i,t)
	Table belonging to settlement period to forecast	A_B(i,t)
	System marginal price (for UK it is for each half of an hour)	smp(i-21,t), smp(i-14,t), smp(i-7,t-1), smp(i-7,t), smp(i-7,t+1), smp(i-1,t-1) , smp(i-1,t), smp(i-1,t+1)
Output	System marginal price	smp(i,t)
Other **parameters**	Day to forecast	I
	Settlement period to forecast	T

The writers used different network topologies and they calculated the mean absolute percentage error (MAPE) for each simulation. Additionally, they filtered the data in their publication in 1998 [25] and forecasted holiday days separately (Saturday, Sunday, and other holiday days), where they used three different templates and established different network topologies. The methodology and input set tracked in these studies became an example for following studies.

Szkuta et al. [26] also tried to forecast the output price with respect to past prices, demand, and capacity data as well as specific information related to the calendar (day code, season, holiday code, etc.) for the power market in Victoria, Australia. Gao et al. [27] added weather conditions and fuel prices to this input set.

Yamin et al. [28] reached a forecasted price result by presenting similar input data for their own network. In this study, they particularly preferred to set an upper limit for extra-high values of input data in order to prevent effects of price spikes on the forecast. They applied the following operation to the inputs before driving them to the network:

$$P_{new} = \begin{cases} P_{old} & \text{if} \quad P_{old} \leq P_{upper} \\ P_{upper} + P_{upper} \ln\left(\frac{P_{old}}{P_{upper}}\right) & \text{if} \quad P_{old} > P_{upper} \end{cases} . \tag{1}$$

Here, P_{upper} is the boundary limit of input price. After this operation they reached more successful results when they used the new clipped input set. Moreover, they examined the effect of size of training set on the power of forecasting.

Rodriguez and Anders [29] first used a pure ANN and then a neuro-fuzzy method, and the finally an ANN considering system congestions. They compared performances of all three methods for their results.

Following all these efforts, studies using only ANNs [30–32], neuro-fuzzy solutions [33–35], and hybrid models [18,19,36] were developed.

In this study, forecasting of the day-ahead price with an ANN is examined and it is tried to evaluate network performance on the success of MAPE results with respect to different topologies, input sets, and training algorithms. In addition, ARIMA modeling, which is one of the most common forecasting methods in the literature, was also used for comparison of the error performance of price modeling with an ANN.

2. Establishment and modeling of the ANN

2.1. Input set for the ANN

For the right modeling, a reliable data pool should be presented. In similar studies, model data were selected carefully and submitted to the system as input in order to get the right response from the ANN. In the work of Aggarwal et al. [20], in which studies from the literature were reviewed and assessed, the most common input data used for estimation of electricity prices via ANNs were historical load, available capacity information (nuclear, thermal, hydro, etc.), forecast load/demand, temperature, settlement period, day code, season code, and historical prices.

Even though almost all of these data can be used in modeling for prices realized in the pool market, the most often used have been data on historical/past prices. In addition, the second significant data set has been the amount of demand.

2.2. Model for the ANN

For the established feedforward backpropagation multilayer ANN, the target system day-ahead price (SDAP) of the relevant day and hour is called $\mathrm{p}_{d,h}^{forc}$. The corresponding input set is $\mathrm{p}_{d-n,h}$, the past SDAP of the same hour n days before; $\mathrm{p}_{d-7m,h}$, the past SDAP at the same hour and on the same type of day (e.g., if the day to forecast is Monday, $\mathrm{p}_{d-7m,h}$ represents preceding Mondays) m weeks before; $\mathrm{t\_avg}_d$, the weighted average value of temperatures in cities (Ankara, İstanbul, İzmir) whose population is more than 3,000,000 for the relevant day for which estimation is going to be performed; $\mathrm{ce}_{d,h}$, consumption estimated for the day and the hour that will be estimated; $\mathrm{bc}_{d,h}$, the amount of bilateral contracts realized for the day and the hour that will be estimated; $\mathrm{a\_cap}_d$, total available amount of capacity (thermal, hydro, and wind) respectively for the relevant day; and $\mathrm{d\_c}_d$, the code of the relevant day. New input sets are formed by adding and subtracting the data explained above, and then effects of the new input sets on the model's forecasting power and error results are studied.

The ANN resulting from the finalized input set is formulated and designed as shown in Figure 2.

The input set consists of data from 01/12/2009 to 07/11/2010, for 342 days in total. Modeling is done with MATLAB software, and for each configuration, the model is run five times separately and the best performance result is recorded for each.

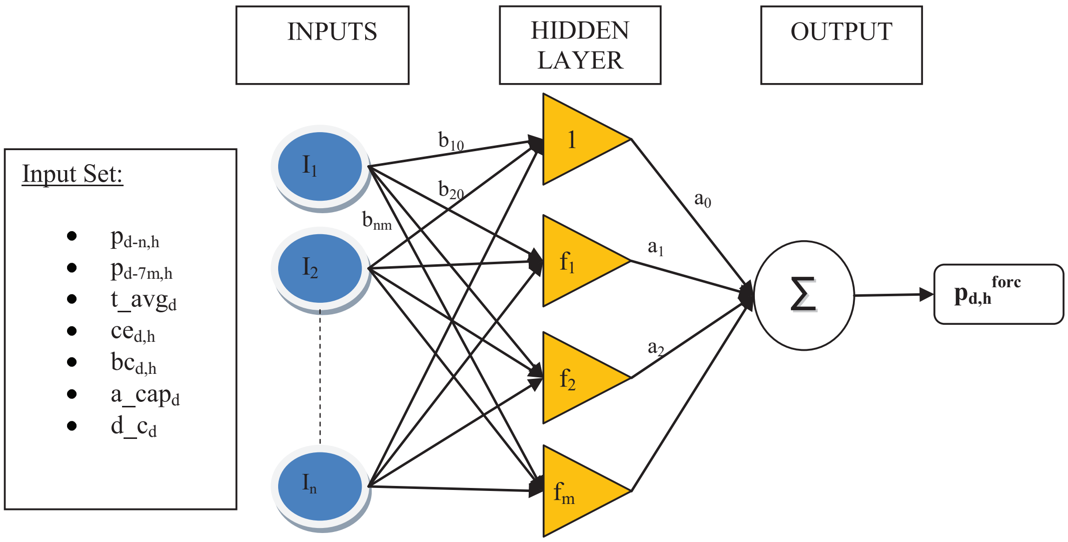

Figure 2. Structure of the network and input set.

Like in some other studies [24,26], when the inputs used in the network model are historical prices, the best explanatory values of that price series are used. In the selection of these data, it will be sufficient to look at a 5-week autocorrelation function of data on historical prices (Figure 3). As can be seen, for any hour, there is high correlation between that hour and neighboring hours, the same hour of previous days (lag 24 and multiples), and same hour of 1, 2, and 3 weeks before that day (lag 168 and multiples).

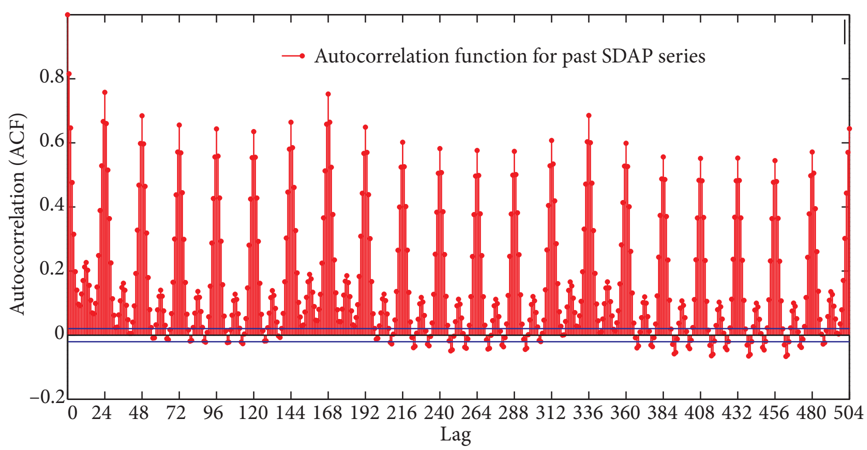

Figure 3. Autocorrelation function for past 5 weeks' system day-ahead price data.

In the established model, different trials are conducted based on the five factors listed below:

1. Type and structure of input,
2. Learning algorithm,
3. Topology of network (number and order of neurons),
4. Number of hidden layers,
5. Activation function.

MAPE values recognized according to these models are calculated as general and weekly based on 1920 h in the test set of 80 days as follows.

Overall:

$$Overall\,MAPE = \left(\frac{1}{1920} \sum_{i=1}^{1920} \left| \frac{e_i}{Actual_i} \right| \right) \times 100; \tag{2}$$

weekly:

$$Weekly\,MAPE = \left(\frac{1}{168} \sum_{i=1}^{168} \left| \frac{e_i}{Actual_i} \right| \right) \times 100; \tag{3}$$

where *e=Actual-Forecasted SDAP*.

MAPE calculations are done for 11 weeks totally. After all trials, the results in Table 2 are obtained.

3. ARIMA modeling

The widely used forecasting method ARIMA was utilized for performance benchmarking for neural networks.

In [4] and other works in the literature on ARIMA, modeling is based on Box–Jenkins analysis. Modeling consists of 4 basic steps that can be listed as follows:

Step 1: First model is formulated as a hypothesis.

Step 2: Based on observations, a specific model is formed by some variables.

Step 3: Model parameters are estimated.

Step 4: Model performance is tested by some criteria. If test is positive then forecasting model is accepted. Otherwise, model is refused and procedure is repeated beginning from Step 2.

In our model that is based on SDAP, first an ARIMA model was chosen, and it was assumed that ARIMA variables would successfully forecast the prices:

$$\underbrace{p_t = c + \beta_1 p_{t-1} + \beta_2 p_{t-2}}_{\text{Autoregressive Model (AR)}} + \ldots + \underbrace{\varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2}}_{\text{Moving Average Model (MA)}} + \ldots \tag{4}$$

Autoregressive Model (AR) Moving Average Model (MA)

Here, p_t represents the forecasted price (for corresponding day and hour), p_{t-d} represents the "d" hour lagged price values, β_t represents price coefficients, ε_t represents error, and θ_t represents error coefficients.

For appropriate modeling, it must be ensured that the time-series data are stationary. In this regard, a unit-root test is commonly used to verify that data are stationary. The Dickey–Fuller unit-root test results for our data are indicated in Table 3.

According to the results shown in Table 3, the unit-root test hypothesis is rejected with 99% confidence, meaning that the data set is stationary and there is no need to take differences.

In order to determine which variables to use in the model, autocorrelation (AC) and partial autocorrelation (PAC) functions of the series are very helpful. The AC function is shown in Figure 3. The PAC function of the price series is given in Figure 4.

Table 2. (a) Result table for ANN model.

No. of hidden layers	Order of neurons	Activation function	Learningalgorithm	Type of input	Weeks 1, %	2, %	3, %	4, %	5, %	6, %	7, %	8, %	9, %	10, %	11, %	Overall %
1	11 × 11 × 1	Tansig	Levenberg–Marquardt	P. SDAP	14.64	8.31	9.92	18.62	7.19	15.00	9.75	11.54	10.35	10.87	21.81	12.54
1	11 × 22 × 1	Tansig	Levenberg–Marquardt	P. SDAP	14.83	8.27	10.68	18.37	7.63	14.52	10.19	11.98	11.64	10.86	23.62	12.91
1	11 × 23 × 1	Tansig	Levenberg–Marquardt	P. SDAP	18.44	12.92	15.63	18.79	7.58	14.60	12.12	12.13	12.48	11.86	25.41	14.59
1	11 × 4 × 1	Tansig	Levenberg–Marquardt	P. SDAP	15.31	8.49	10.73	16.80	8.35	14.08	11.63	11.62	12.95	11.00	24.15	13.10
1	11 × 9 × 1	Tansig	Levenberg–Marquardt	P. SDAP	16.11	8.85	11.52	18.82	8.30	13.78	11.67	12.54	11.63	11.79	24.44	13.47
2	11 × 11 × 11 × 1	Tansig	Levenberg–Marquardt	P. SDAP	14.05	7.77	10.47	19.02	7.68	14.08	10.43	11.68	12.20	10.88	23.25	12.85
2	11 × 11 × 4 × 1	Tansig	Levenberg–Marquardt	P. SDAP	14.56	8.06	11.47	18.95	8.52	14.13	10.39	11.77	12.05	10.95	23.15	13.05
2	11 × 11 × 20 × 1	Tansig	Levenberg–Marquardt	P. SDAP	18.75	8.16	11.49	19.25	8.59	13.95	10.92	11.82	12.11	11.09	24.52	13.61
1	11 × 11 × 1	Linear	Levenberg–Marquardt	P. SDAP	12.76	7.74	11.41	18.47	9.18	15.20	11.35	12.44	11.09	11.25	22.27	13.04
1	11 × 11 × 1	Logsig	Levenberg–Marquardt	P. SDAP	13.96	7.42	10.03	19.32	7.05	13.90	10.41	11.69	11.28	10.56	22.87	12.61
1	11 × 11 × 1	Tansig	Simple gradient descent	P. SDAP	33.20	11.06	13.89	23.11	15.27	25.46	21.28	21.13	26.27	24.77	30.29	22.29
1	11 × 11 × 1	Tansig	Ada.lea. rate & mom. grad. descent	P. SDAP	18.25	9.03	11.83	18.47	8.60	16.40	12.67	12.63	12.20	12.68	23.58	14.22
1	11 × 11 × 1	Tansig	Levenberg–Marquardt	P. SDAP+ Con. For.	13.02	8.07	9.20	14.76	10.06	12.54	12.21	12.94	12.70	12.40	22.71	13.15
1	11 × 11 × 1	Tansig	Levenberg–Marquardt	P. SDAP+ Bil. Con.	15.89	9.22	10.83	17.36	7.73	13.58	11.49	11.40	13.29	11.23	23.90	13.16
1	11 × 11 × 1	Tansig	Levenberg–Marquardt	P. SDAP+ Ava. Cap.	15.78	7.72	10.05	18.70	9.37	14.94	10.31	11.87	12.68	11.70	23.44	13.19
1	11 × 11 × 1	Tansig	Levenberg–Marquardt	P. SDAP+ Temp.	16.45	8.89	9.81	18.91	7.24	16.16	10.69	11.25	11.81	11.04	22.58	13.08
1	11 × 11 × 1	Tansig	Levenberg–Marquardt	P. SDAP+ Day Code	13.87	9.64	11.94	18.70	7.49	14.12	10.38	12.60	11.66	11.35	24.03	13.25
1	11 × 11 × 1	Tansig	Levenberg–Marquardt	Clipped P. SDAP	6.83	5.48	8.76	17.65	7.80	13.99	10.98	12.13	11.57	10.88	22.77	11.71
1	11 × 11 × 1	Tansig	Levenberg–Marquardt	Clipped P. SDAP	12.82	7.17	9.78	17.49	7.39	14.18	10.21	11.96	11.43	11.02	22.68	12.35

Table 2. (b) Abbreviations list for (a).

Tansig	Tangent sigmoid
Logsig	Logarithmic sigmoid
Ada. lea. rate & mom. grad. descent	Adaptive learning rate with momentum coefficient gradient descent
P. SDAP	Past system day-ahead price
Con. For.	Consumption forecast
Bil. Con.	Bilateral contract
Ava. Cap.	Available capacity

Table 3. Augmented Dickey–Fuller unit-root test results.

Null hypothesis: SGOF has a unit root	
	t- Statistic
Test critical values	–5.536706
1% level	–3.431311
5% level	–2.861850
10% level	–2.566977

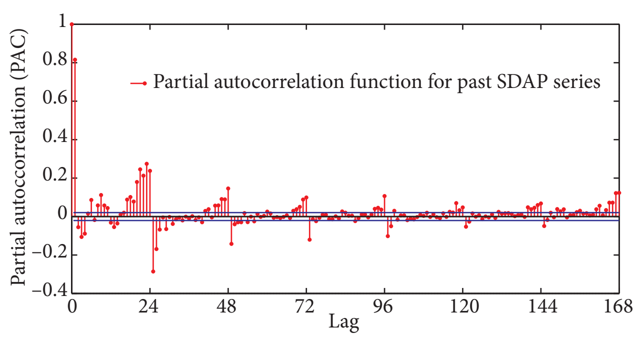

Figure 4. Partial autocorrelation (PAC) function.

If the AC function is geometrically decreasing while the PAC function fades out after having a large value in the first difference (as in Figures 3 and 4), then the series is an AR(p) series. On the other hand, some other variables can be used, similar to the ones in the neural network model's input set. Lagged values of price like p_{t-2}, p_{t-3}, p_{t-24}, f_{t-48}, p_{t-72}, p_{t-168}, p_{t-336}, and p_{t-504} are among such variables seen in the literature. In our model, a moving average is not used, the model is based on the autoregressive part, and variables are utilized accordingly.

Table 4. Model coefficients.

Model coefficients	c	β_1	β_2	β_3	β_4
	–78.1450	0.3301	0.1673	0.2451	0.2779

There are studies in literature that used these price differences in the models corresponding to Step 3. However, the applicability of this approach to forecasting is not questioned although error performances are discussed extensively. More precisely, the first difference of the time series cannot be used in forecasting because price information of the last hour is not available in real life. Only data from the last 24 hours (i.e. yesterday) are accessible while forecasting. Therefore, an AR model is formed as in Eq. (5).

$$p_t = c + \beta_1 p_{t-24} + \beta_2 p_{t-48} + \beta_3 p_{t-168} + \beta_4 p_{t-336} \tag{5}$$

Calculated coefficients of this model are given in Table 4.

All of the coefficients are smaller than 1, their sum is close to 1, and confidence intervals are greater than or equal to 85%. The R^2 value is around 75%, meaning that the model can be regarded as representing the data. Actual and forecasted price values of 3 chosen weeks in this model are depicted in Figure 5.

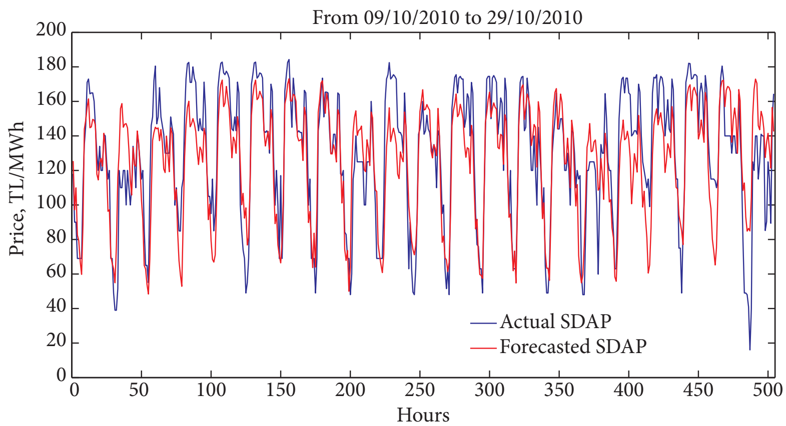

Figure 5. ARIMA forecasted and actual SDAP.

Forecasting performance of this AR model can be analyzed further as follows by looking at the MAPE values of 3 weeks in Table 5.

Table 5. MAPE of 3 weeks.

Weeks	MAPE
Week 1 (9–15 Oct 2010)	13.78%
Week 1 (16–22 Oct 2010)	12.49%
Week 3 (23–29 Oct 2010)	20.54%
Average	15.60%

As seen in Table 5, the model makes a reasonable yet unsuccessful forecast in cases where there are extreme values (i.e. sharp peaks and dips). On the other hand, there are more successful results in studies like those of Contreras et al. [4], Conejo et al. [1], Weron and Misiorek [9], and Jakaša et al. [37] since lags of shorter than 24 are used. Similarly, if the first and second differences are included in our model as in Eq. (6), then error values become as in Table 6.

$$p_t = c + \beta_1 p_{t-1} + \beta_2 p_{t-2} + \beta_3 p_{t-24} + \beta_4 p_{t-48} + \beta_5 p_{t-168} + \beta_6 p_{t-336} \tag{6}$$

As seen in Table 6, results are significantly improved after including the first and second differences of the price in the model. However, notice that these types of models having minimized error values cannot be used for forecasting since lags of shorter than 24 correspond to data that are not available in the day ahead.

Table 6. MAPE of 3 weeks (with first and second lags).

Weeks	MAPE
Week 1 (9–15 Oct 2010)	10.56%
Week 1 (16–22 Oct 2010)	10.87%
Week 3 (23–29 Oct 2010)	14.33%
Average	11.92%

4. Conclusions

During the training process, different network topologies were tested and error performances of networks having different numbers of neurons and layers were analyzed. Parameters like training algorithm and activation function were altered and it was questioned whether these parameters decreased the error rate or not. Furthermore, a price-clipping method was applied to extra-high inputs and then the effect of the new input set on network performance was observed.

According to findings from trials, historical price data are seen as the most effective inputs that decrease the network's forecasting error. Average temperature data had better results in comparison with data like consumption forecast, amount of bilateral contracts, and day code.

While the most successful training method was the Levenberg–Marquardt algorithm among others, tangent hyperbolic and logarithmic sigmoid functions gave similar error performances as an activation function.

Successful network and training algorithm choice could be summarized as follows:

Number of hidden layers:	1
Number of neurons in hidden layer:	11
Activation function:	Hyperbolic tangent
Learning method:	Levenberg–Marquardt
Input set:	Clipped past SDAP values

On the other hand, these results do not imply that an ideal network design has been achieved and there is no certain topology determination algorithm for ANNs.

Moreover, the model built via the ARIMA approach, which has been mostly used in literature, produced a less successful error performance (Table 7).

Table 7. Comparison of ANN and ARIMA.

Weeks	ANN	ARIMA
Week 1 (9–15 Oct 2010)	20.84%	13.78%
Week 2 (16–22 Oct 2010)	7.72%	12.49%
Week 3 (23–29 Oct 2010)	13.90%	20.54%
Average	14.15%	15.60%

This study is a pioneering study for the Turkish electricity market since it is the very first neural network approach for forecasting the spot market price. It suggests an ideally constructed neural network as a nonlinear forecasting method and shows that the neural network model gave better results over a time-series model.

In other ongoing studies of estimation of price in the literature, mixture/hybrid structures have been started to be used; modeling by time-series analysis and regression approaches combined with ANNs has been preferred. Different studies like estimation of price classification [38] and price spikes [39] have also kept up-to-dateness. The ANN model presented in this study could be developed further by utilizing price classification and spikes, and could be applied to SDAP forecasting.

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