A Combined Seasonal ARIMA and ANN Model for Improved Results in Electricity Spot Price Forecasting: Case Study in Turkey

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Abstract- **Developing countries are trying to improve the competitiveness of the energy markets with continuous liberalization. This makes the market highly sensitive. Every player in the market has a greater need to know about the smallest change in the market. Hence, ability to see what is ahead is a valuable advantage to make the right move. A time series forecasting with the smallest errors would be a powerful tool for the energy producers. This paper proposes combined methodology in time series forecasting. Generally accepted and widely used ARIMA and ANN with backpropagation learning are combined. The methodology is implemented for the day-ahead Turkish power market. It is observed that the proposed methodology gives results with reduced errors. The achievements are compared with conventional use of both ARIMA and ANN.**

I. INTRODUCTION

Liberalization of energy markets has been continuing in countries with developing industries. China has become the hot point of energy demand for the last few years; now, India is expected to be the pioneer to lead the global energy markets. Turkey is still growing and the energy markets are changing. Stabilized markets have less commercial sensitiveness than the growing markets. The energy producers, regulators, vendors and consumers of energy markets in developing countries are in need of closer look ahead. Commercial flexibility can only be provided by timely and successful predictions.

In Central Western Europe (CWE) power markets' non-discriminatory data transparency allows most market players to run fundamental model market models to forecast short-term (day ahead, weak ahead and month ahead) power prices and also medium term power prices (quarters, half-years, calendar-years). Unfortunately, achieving the data transparency is only possible when the liberalization is finalized and the market is stabilized.

Another way of forecasting power prices, time series based models like Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA) and Artificial Neural Networks (ANN) are preferred when time series of historic prices are used. These methods certainly lack the ability to catch all price spikes or price decreases due to changes in fundamental drivers but offer a way to have a stable expectation of tomorrow's power prices.

In a competitive power market it becomes important for the market players who have flexibility in their assets to have a view on the future prices. Hydro electrical Power Plants (HPP) with dams for instance, can store a certain amount of water constrained by the dam's maximum capacity to produce electricity when the price is high. In Turkey, where we have completed the case studies, 25.5% of electricity demand is met by HPP [15]. Being the most utilized source after thermal energy when meeting energy demand, hydropower has a valuable role in Turkey. Moreover, undeveloped capacity reaches up to %64 of the economically reasonable hydro capacity in Turkey [1]. This reliance on hydro is one motivation to come up with a price forecasting methodology for the Turkish power market.

This study aims to propose a combined method of short term price forecasting for the electricity spot markets. The most widely used SARIMA considering the seasonal residues and multi-layer forward feeding ANN with Backpropagation (BP) learning are hybridized in order to reduce the errors in forecasting results. The proposed method is applied for the case of Turkey.

This paper is organized as follows. A short overview of price forecast studies is given in the second section. Third section will be saved for reviewing the methods used before the model is proposed in section 4. The application and results will be presented in section 5 and finally, the conclusion will be given in section 6.

II. LITERATURE REVIEW

Time series forecasting shows different features by the time horizon studied and the market data used. When the time horizon is considered, the forecast can be as short-term (day ahead, weak ahead and month ahead), medium term (quarters, half-years, calender-years) or long term (more than ten years ahead).

Numerous forecasting methodologies for day-ahead power forecasting have been developed, each considering the market specifications. The market regulations, energy distribution and share would be the features considered.

The model selection should be done only after the decision criteria are set. The chosen model can be adjusted for the corresponding power market. Weron's study [17] provides an overall knowledge about electricity price forecasting.

The Fundamental Modeling allows a comprehensive analysis suitable for marginal cost power markets. Using the fundamental modeling, the effects of relationship between physical side and economical side on energy generation and trading are analyzed. Fundamental drivers like weather conditions, hydro power capacity and economical drivers like foreign exchange rate, import/export balance, coal prices, government owned power plants are taken into account all along with the correlations between them.

According to Weron [17], modern statistical models forecast future prices by using mathematically combined previous prices and exogenous variables. Time series forecast method SARIMA is examined under statistical models. The statistical models differ from fundamental models not only by explaining part of data, but also predicting the unexplainable part as a sequence of past observations without a comprehensive approach.

Intelligent models on the other hand, are known for their non-parametric features and ability to identify non-linear connections between given data sets using transfer functions. These methods bring up learning, evolution and fuzziness factors together [7]. ANN modeling has a success proven image as a to be very short-term forecasting tool. An ANN model can be used to express the functional relationship between covariates (inputs) and response variables (outputs) with high complexity that can be identified based on optimization methods [9].

Lindberg [12] used SARIMA process for price forecasting in Nordic power market. The price in a given time is considered to be sum of several linear components. Then these components are forecasted using regression to SARIMA models and combined to have the final prediction.

Multiple points ahead forecasting with ANN is studied, using similar days approach for the required data to forecast future prices [13]. Considering the effective and efficient results of two separate models, ANN and ARIMA processes have been studied as hybrid models as well. Different models were developed believing that a time series is a sequence of linear and non-linear relationship within the series.

Zhang [18] proposes the first hybridization of ARIMA and ANN as a two-step approach, where the response variables (outputs) are defined by linear and non-linear components. Zhang's study shows that a hybrid model of ARIMA-ANN is applicable in time series forecasting. Khashei and Bijari [10] use a similar approach and get better results in multiple points ahead forecasting. Lasheras et al [11] has predicted the copper spot prices using recurrent neural networks and ARIMA. Chaâbane [6] uses a similar hybridization for electricity price forecasting after having decomposed the data into linear and non-linear components. For linear components Auto Regressive Fractionally Integrated Moving Average (ARFIMA) is used, where as ANN keeps its role in non-linear part. All besides, there are numerous studies in the literature that hybridization is mostly utilized to avoid the weaknesses of single models.

It is concluded that the correction for the forecasting weakness in seasonality and linearity are not both handled together.

III. METHODOLOGY AND DATA

A. Methodology

The fundamental method is proven to be more comprehensive but cannot be applicable in developing countries because the completeness of data is not assured and historical data is used [14]. A time series forecasting method, SARIMA, is preferred in such markets and fast results are achieved. ARIMA is mathematically defined by Anggraeni et Al [3] as follows:

1. An autoregressive process with the order p $\mathrm{Z_t}$ is predicted value at t time, $\mathrm{Z_{t-p}}$ history data at (t-p) time and is estimated parameter:
$$Z_t = a_1 Z_{t-1} + a_2 Z_{t-2} + \cdots + a_p Z_{t-p} \quad \textbf{(1)}$$

2. Moving Average models provide forecasts based on previous forecasting errors where Z_t can be predicted at time t with Z_{t-q} approximate error at time (t-q), and is an estimated parameter β:
$$Z_t = \beta_1 Z_{t-1} + \beta_2 Z_{t-2} + \cdots + B_q Z_{t-q} \quad \textbf{(2)}$$

3. The two are combined together with an estimated stationary parameter of $\theta 1$:
$$Z_t = \theta_1 Z_{t-1} + Z_t - \theta_1 Z_{t-1} \quad \textbf{(3)}$$

4. Autoregressive Integrated Moving Average (ARIMA) is then achieved by considering the differences in time becomes:
$$\phi_0(B)(1-B)^d Y_t = \theta_0 + \theta_0(B) a_t \quad \textbf{(4)}$$

5. Adding the seasonality factor D and dependence on the average it becomes SARIMA by assuming that the time series is distributed normally [16] with
$$\{Z_t\} \sim WN(0, \sigma^2) \quad \textbf{(5)}$$
$$\varphi(B)\phi(B^s)(1-B)^d(1-B^s)^D(Z_t - \mu) = \theta(B)\Theta(B^s)a_t \quad \textbf{(6)}$$

ANN, an intelligent model to increase accuracy as it is proposed by Babu [4] that a hybrid ARIMA-ANN model has shown to be better than both conventional ARIMA model and ANN model separately.

What makes ANN different is that it can catch the non-linear relationship between data rather than explaining an observation as a linear sequence of past values as in SARIMA case. This feature is observed clearly in application of the multi-layer feed-forward network structure. When discriminant is to be non-linear in a complex problem, a perceptron with a single layer fails to solve the problem since it can only approximate linear functions of the input. This limitation is resolved by adding hidden layers between input and output layers to construct a more complex connection. At this stage, model turns into a MLP (Multilayer Perceptron) [2]. In Mandal's study [13] the price at time $t + h$ is forecasted using price at time t, load at time t, and price averages of the similar days, as explained in the study, for each hour until $t + h$ are put as inputs.

In supervised back propagation learning, gradient chain is applied using the transfer function, which is generally sigmoid [2]:

$$f(u) = 1/(1+e^{-u}) \tag{7}$$

$$E = \frac{1}{2}\sum_{l=1}^{L}\sum_{h=1}^{H}(o_{lh} - y_{lh})^2 \tag{8}$$

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial o_i}\frac{\partial o_i}{net_i}\frac{\partial net_i}{\partial w_{ij}} \tag{9}$$

$$w_{ij}^{t+1} = w_{ij}^{t} - \eta\,\frac{\partial E^t}{\partial w_{ij}^{t}} \tag{10}$$

B. Data

The best sources we can get data from are EPIAS and TEIAS who are providing us with DAP (Day-Ahead Prices), supply and demand information in roughly detailed format. Only the price and demand are given in hourly resolution.

24 price observations for each hour in a day are recorded using 2014-2015 data. That is, the model will be based on two-years of hourly data; approximately 8760*2 = 17520.

The gathered data is decomposed as clearly seen in Fig. 1. The data is composed of three components: seasonal component, trend component and random component as mentioned in the market structure. This enables the application of the Box-Jenkins model.

IV. MODEL

In this paper, we propose a hybrid ARIMA-ANN model due to the effective results of the combination of the two techniques that we discussed above in the literature review. In order to construct a seasonal ARIMA model, the time series data is processed using the very well known Box-Jenkins method, which consists of three steps: identification, estimation and verification. The details regarding Box-Jenkins method are given in the model description. After verification, the residuals of the fit SARIMA model are used as inputs for the ANN model. The purpose of this final step is to forecast the error sequence of the fit model, which cannot be defined using a linear method like SARIMA. Then, the sum of the results of both SARIMA and ANN forecasts is considered to be the final forecast. These steps are illustrated in Fig. 2 and will be given in more details in the case section. The structure of the model is illustrated in Fig. 2.

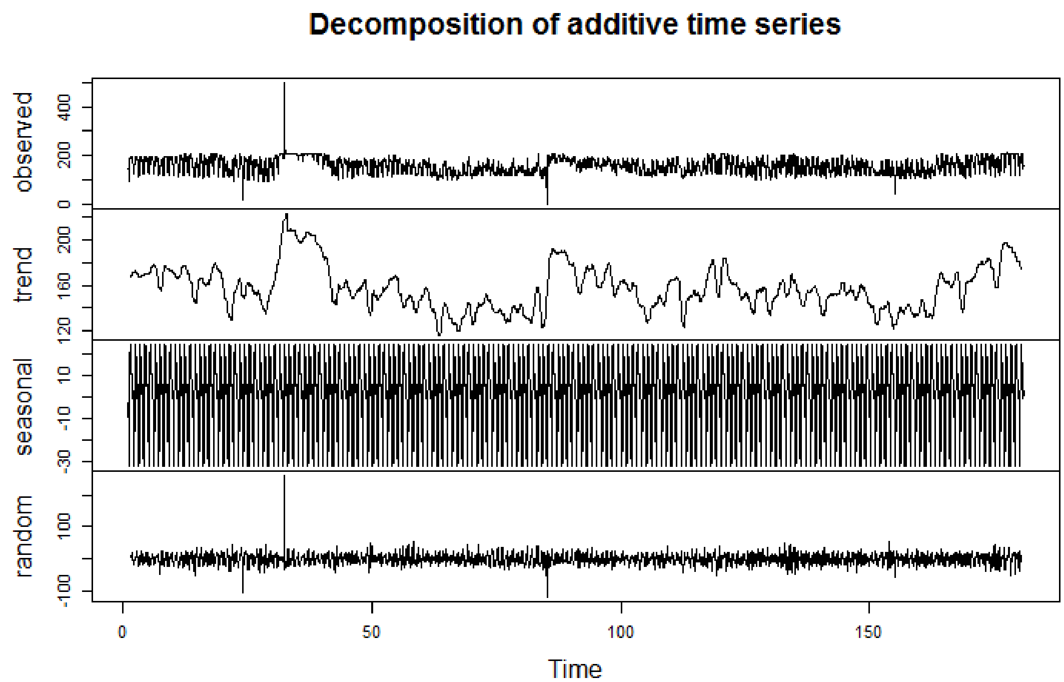

Fig. 1: Decomposition of time series of the model for identification of components (DAP prices belong to first half of 2014 are represented)

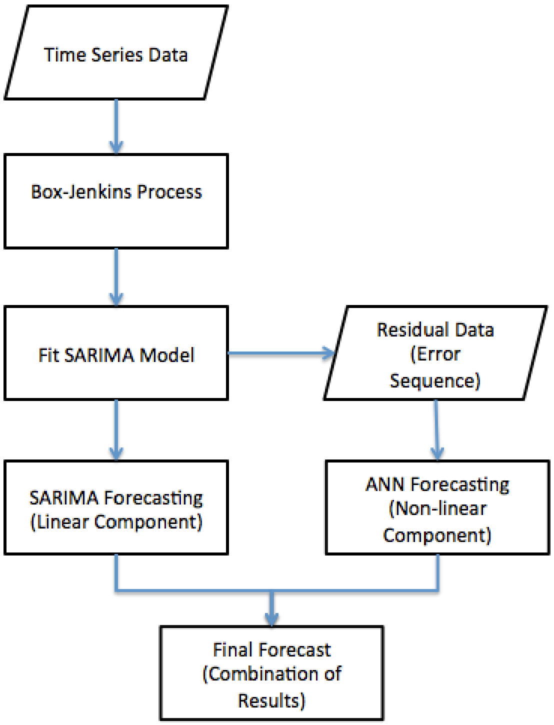

Fig. 2: Flowchart of the model

The time series $\{y_t\}$ is considered as a function of a linear and a non-linear component. In general,

$$y_t = f\ (L_t, N_t\ ) \quad \textbf{(11)}$$

and

$$y_{t,actual} = y_{t,prediction} + \varepsilon_t \quad \textbf{(12)}$$

L_t is the forecast results of fit SARIMA model in the linear part of the equation. For the non-linear component, N_t denotes the error sequence of this fit model. Therefore, there are two forecast steps in our proposed methodology. In the first one, the times series data $\{y_t\}$ is expressed as a linear sequence of the past observations. The residuals of this fit model, error sequence, are considered to be the non-linear part and are explained by ANN model where

$$\varepsilon_t = N_t = y_{t,actual} - y_{t,prediction} \quad \textbf{(13)}$$

A model with described structure is preferred due to the reasons mentioned earlier, that an ARIMA process, though it is widely practiced, might be insufficient depending on the time series analyzed and fails to explain some parts of the data linearly. However, when combined with an ANN model, as seen in the previous practices, such model can give very accurate results thanks to ANN's capability in explaining the non-linear parts of the data.

As illustrated in Fig. 2, the first step of the proposed model is applying Box-Jenkins process on the time series data. In order to apply Box-Jenkins method, an observation at time *t* is considered as in equations **(1)** and **(2)** respectively. Then, as proposed by Lindberg, linear component as defined, is divided into two sub-components as follows,

$$L_{d,h} = DA_d + HP_{d,h} \quad \textbf{(14)}$$

where *DA* represents the daily average price for *d = {1, 2, ... N}* and *HP* represents the hourly profile value for *h = {1, 2, ... 24}*, *N* denotes the number of days in the model. *DA* is found simply by taking the average price of the given day; and *HP* is found by taking the difference between realized price value and *DA* for the corresponding day. This adjustment helps both in trend removal and differentiating process. Each *DA* and *HP* values are labeled with the corresponding date so that as we fit the model, each one of them is guaranteed to compile without miscalculation. Therefore, one time series for *DA* values with 7 days of seasonality and seven separate time series for each day of the week with corresponding *HP* values with 24 hours of seasonality are constructed. In the end, forecasted $L_{d,h}$ value is summation of forecasted DA_d and $HP_{d,h}$ values. Steps of the Box-Jenkins process are as follows,

1. *Identification:* Time series data is preprocessed. Tools like ACF&PACF are used to detect dependencies between data. Differencing is applied if necessary to get stationary data.
2. *Estimation:* Inıtial model is chosen, deciding the model parameters *p, d, q*.
3. *Verification:* Residuals of the model are analyzed and checked for white noise situation.

V. CASE: APPLICATION IN TURKISH POWER MARKET

A. Power Market Definition

The Turkish Power Market has been growing rapidly since the start of the liberalization in late 1980's in parallel to creating a competitive environment with numerous producers, wholesalers, retailers and regulatory entities.

Electricity demand is met by the energy generated by different producers and sources (either fossil or renewable). In the European Union both production and storage (as in hydro energy) are cheaper. However, the investors would like to have the flexibility for their decisions. In order to minimize costs they might want to change the electricity generation process and/or resource input.

As can be seen in Fig. 3 and Fig. 4, price is determined where supply meets demand. This determination is separately held for each hour of the day. The elevation represents the increasing supply level as more producers start generation. It is clearly seen in Fig. 3 that there is a bidding process for market players. That is, supply meets demand through this process through which each market player orders to sell or to buy an amount of energy for a certain price interval for the bidding hour of the next day. Regulation authorities evaluate this process so that prices increase to have more supply in the system in order to decrease the gap between supply and demand. In other words, when total supply for a price level is not enough, a higher price level is evaluated to involve more supply. The bidding process through the system ends at 11.00 every day; however, there are no time limitations for the bilateral contracts between the market players. Afterwards, Turkish regulation authorities publish the day-ahead prices at 14.00 every day and keep it committed for 24 hours. The idea behind this process is simple. The goal is to meet demand with the lowest price possible. As a consequence, when renewable generation is not sufficient, thermal power plants fulfill this gap at some cost, which causes higher price levels.

Because of the consumption rates the peak hour and off-peak hours occur. During the off-peak hours (late night and early morning in Turkey) demand is low, but shows volatility.

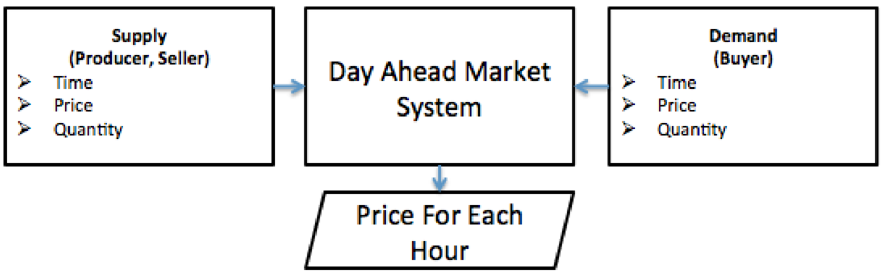

Fig. 3: Aggregated supply and demand results in price determination for each hour

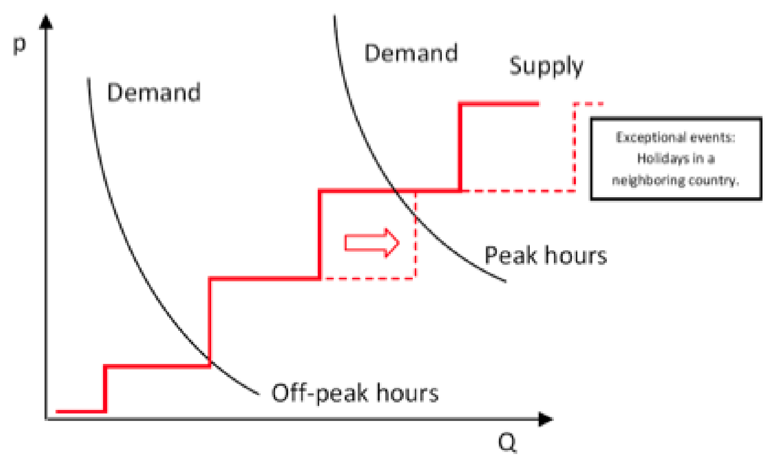

Fig. 4: Supply-demand curve for power markets, indicating the demand met by supply at a level. (Caro G., 2010)

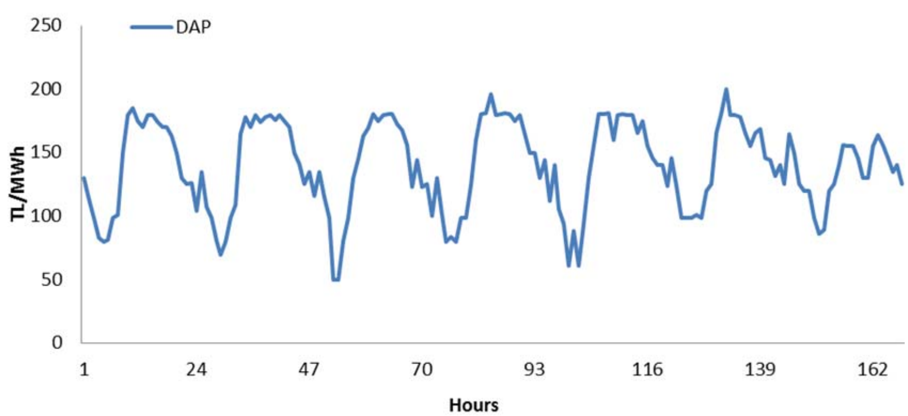

Fig. 5: Day ahead prices for a sample week from 2015

As seen in Fig. 5, the pattern-based fluctuation within a day shows itself in weekly and even yearly resolutions as well. The weekly profile is consistent when there is no special event like national holidays or government interference.

Prices are formed by the interaction of aggregated hourly demand, which is met by the supply. Thus, the price itself is a sequence of various components like base trends, which are driven by a sequence of long term variables like GDP, climate etc., seasonal component, which is a sequence of periodic variables like day-night, summer-winter etc., event component, which is a sequence of holidays and special days, and random component which is caused by unexpected situations like shortage or government interference. This property of the price is also given in Fig. 1.

B. Day Ahead Price Forecasting with the Proposed Model

As explained in section 4 the data will be analyzed in two different parts. First step is the Box and Jenkins application of SARIMA and then the ANN will be applied. After the application of identification, estimation and verifications steps, results are given in Table I.

TABLE I
SARIMA TERMS FOR L_t SUB-COMPONENTS

Component	Model Orders
DA	$(2,1,2)(0,1,1)_7$
HP	$(2,0,1)(2,1,0)_{24}$

Using AIC (Akaike Information Crtierion) and R^2, the best model for each component is chosen. Maximizing the likelihood function, the terms given in Table I are determined for the fit model in estimation step. Afterwards, residuals are analyzed. Examining Fig. 6.a and Fig. 6.b, it is seen that after processing, the residuals of the fit model is better in terms of Gaussian normal distribution. This indicates that a good fit for white noise situation is desired. Fig. 7.a shows that there is a correlation in DA data with 7 days of lag. Also Fig. 7.b shows that there are no dependencies left after fitting SARIMA model. *(Note: QQ Plot and ACF are illustrated only for DA component to set an example that 4 graphs for each day of the week would be too much.)*

In order to run this model, statistical software, R is utilized with necessary packages ("*Performance Analytics*", "*tseries*", "*forecast*" and "*neuralnet*").

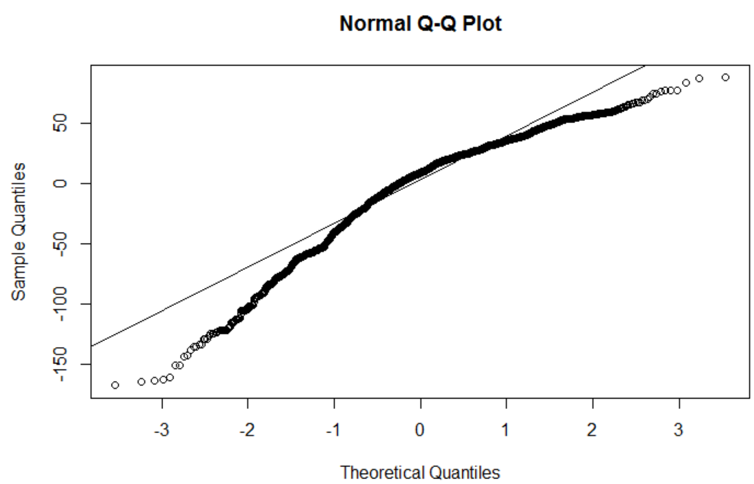

Fig. 6.a : QQ Plot of DA data, indicating the normal distribution(linear line) and daily average component's distribution

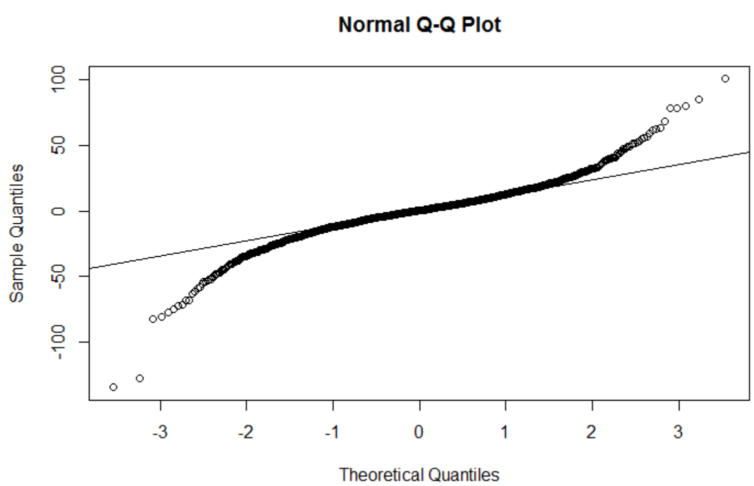

Fig. 6.b : QQ Plot of DA residuals, indicating the fitness of residuals' to the normal distribution

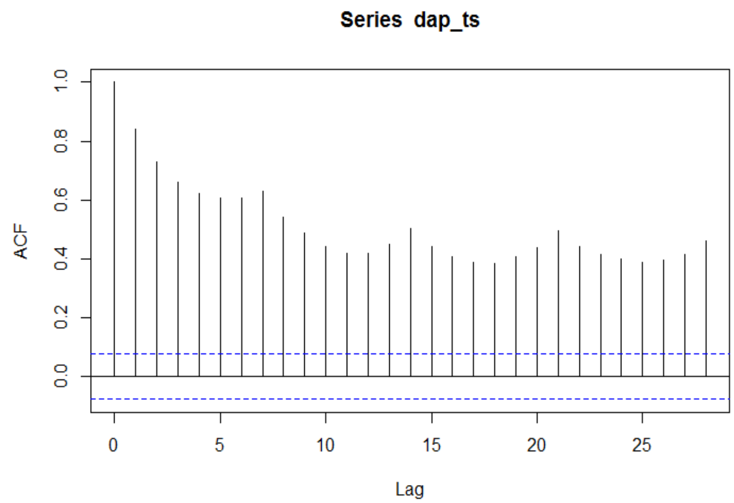

Fig. 7.a : ACF of DA data, where auto-correlation is observed with 7 days of lag

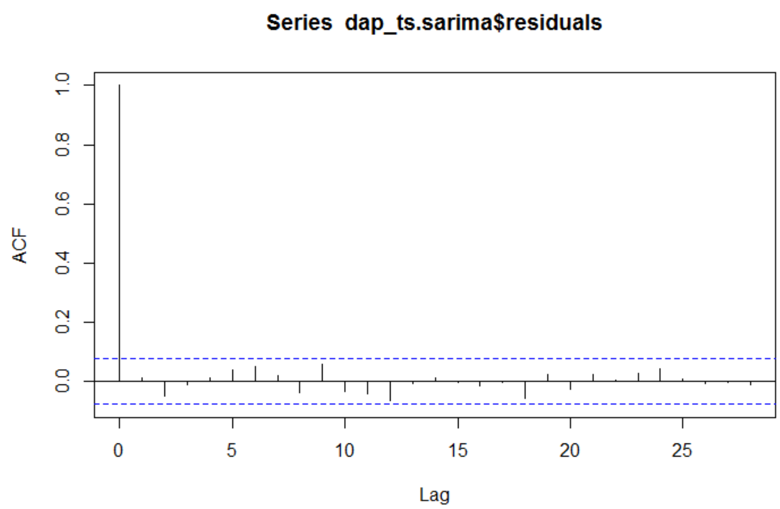

Fig. 7.b : ACF of DA residuals, where there is no auto-correlation left for the residuals of the model

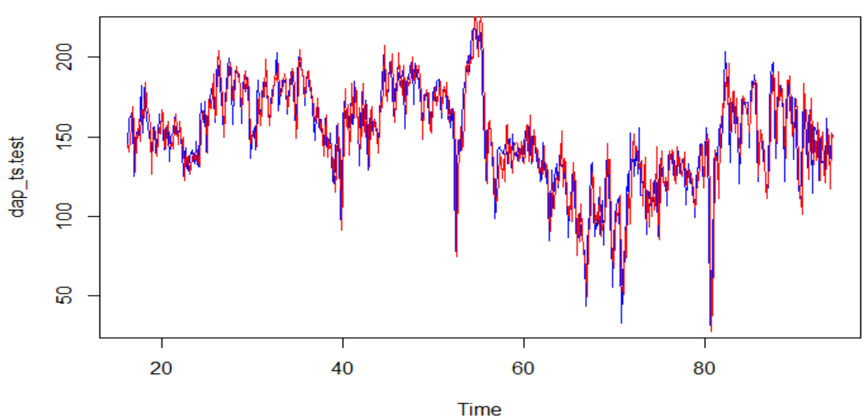

Fig. 8: DA side of the fit model. *Blue* line shows the realized values. *Red* line shows the fit model
(An output graph from R studio)

After fitting SARIMA model, the error sequence of the fit model is considered to be N_t and calculated as in equation **(13)** simply by subtracting. This component of the price is forecasted using ANN.

As forecasting with ANN, there are some limitations. One of them is stated in the power market definition, the prices for the next day are published at once. That is, when forecasting time $t + h$ at time t, most up-to-date data for $t + h$ will be the information of time t. This sort of obstacle is handled using recurrent neural network (RNN) approach. However, for the software program used in this study there is no suitable RNN package found. So, a new pattern for input data is determined. In proposed ANN model, an error sequence at a given time is explained by the error sequence at the same hour of previous day, the error sequence at the same hour of the previous week, the error sequence at the same hour of two weeks earlier and corresponding time factors. Thus,

$$\varepsilon_t = N_t = g(\varepsilon_{t-24}, \varepsilon_{t-168}, \varepsilon_{t-336}, Day\ Factor_t, Time\ Factor_t) + e_t \quad \textbf{(15)}$$

After analyzing the residuals of the fit model, the error sequence time series are classified using "R" software and hours and the days of the week are grouped for certain hours have errors close to "0", where some hours have errors higher than "0". 3 groups for hour and 3 groups for weekdays are constituted with "-1, 0, 1" values.

Fig. 9 illustrates the proposed ANN structure, where input variables are transferred to hidden units with corresponding weights and then using the sigmoid function applied to the input and hidden layer neurons to create the forecast (gradient chain).

Back propagation algorithm is used for supervised learning. Sigmoid function is chosen as the threshold function. The best structure is found to be as N (5,7,1). Model is trained using 30 days of shifting data (30*24=720). That is, for each incoming day, the training data is shifted one day forward to cover the current day.

C. Results and Discussions

After finding best possible models for both SARIMA and ANN, the summation of the forecasted values is defined as the final forecast. In order to check the accuracy of the forecasts, both in-sample and out-of-sample tests are held. In-sample test is simply the accuracy of the fit model, while out-of-sample test is real-time forecast for the future. In both cases, forecasts are done for 24 hour ahead and regular SARIMA model and proposed hybrid ARIMA-ANN model are compared using MAPE and MSE values.

$$MSE = \frac{1}{N}\sum_{t=1}^{N}(y_{t,actual} - y_{t,prediction})^2 \quad \textbf{(16)}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_{t,actual} - y_{t,prediction}}{y_{t,actual}}\right| \quad \textbf{(17)}$$

As can be seen in Table II, proposed hybrid model has almost 20% better performance in both sample and out-of-sample tests. Thus, the proposed model can be used by both suppliers and consumers.

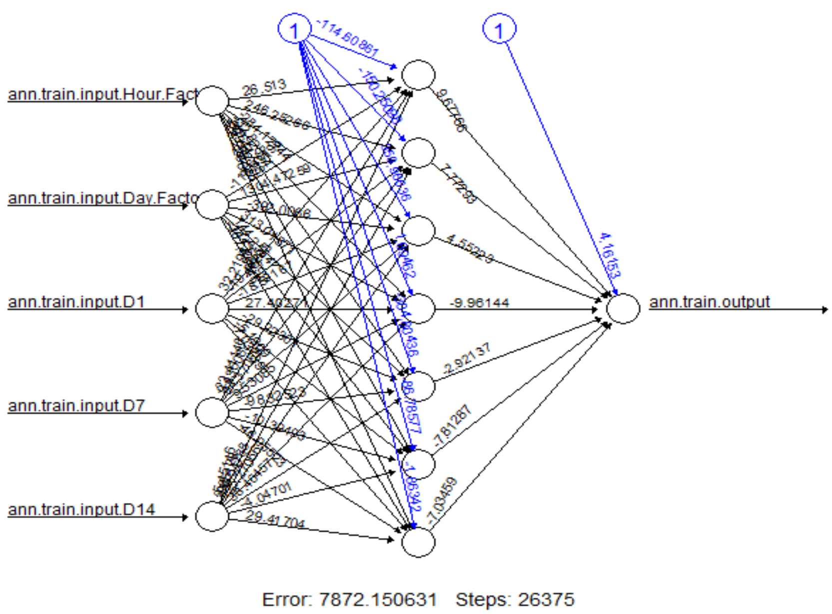

Fig. 9: ANN structure for the proposed model.

TABLE II
COMPARISON OF TWO MODELS

	In-Sample Testing (9 days)		Out-of-Sample Testing (5 days)	
	MAPE	**MSE**	**MAPE**	**MSE**
SARIMA	%5,03	145,97	%13,8	458,07
Hybrid	%4,08	134,25	%10,2	350,57

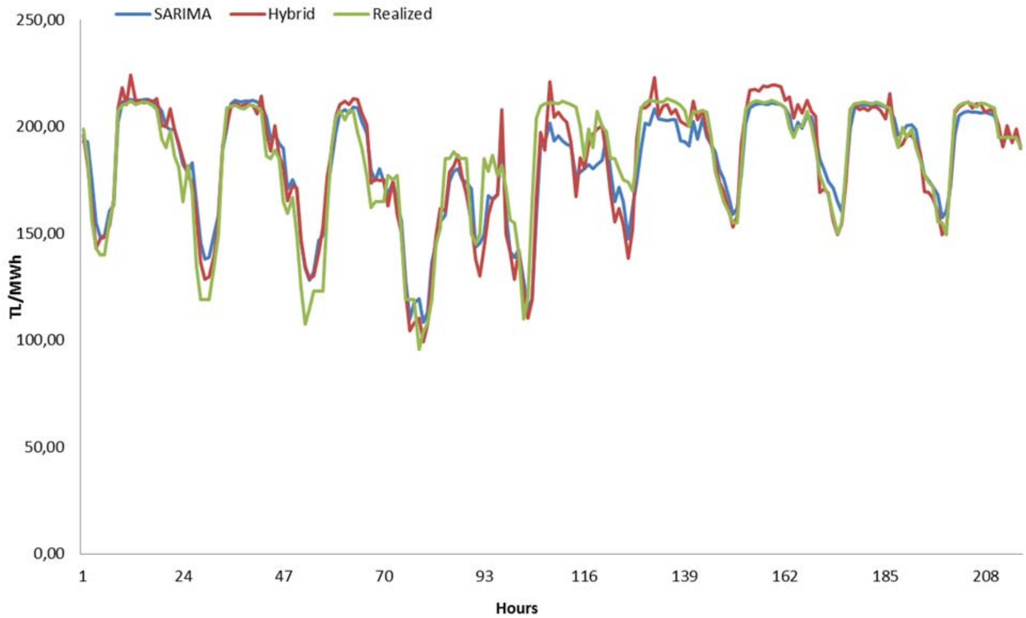

Fig. 10: In-sample testing for 28.08.2014 – 05.09.2014

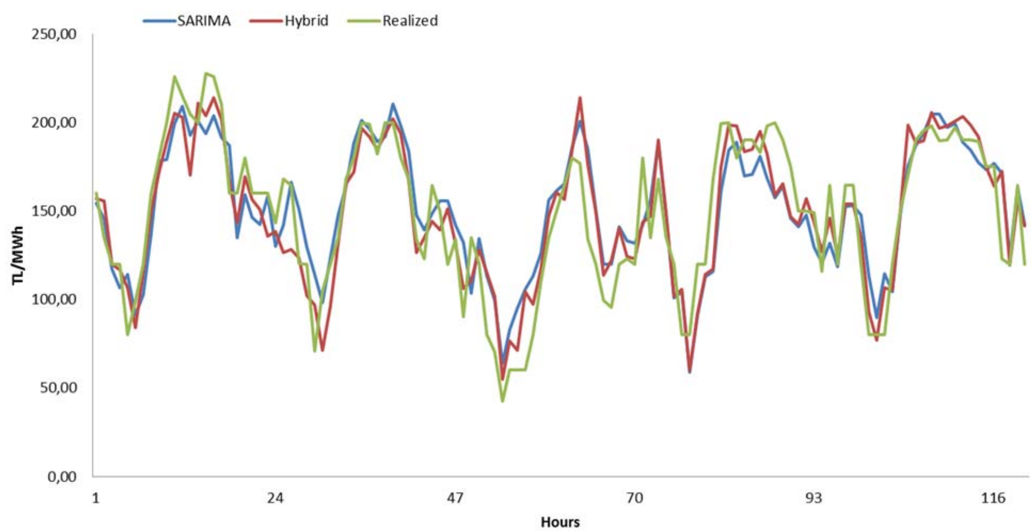

Fig. 11: Out-of-sample testing for 02.10.2015 – 06.10.2015

Fig. 10 and Fig. 11 show in-sample and out-of-sample tests, respectively. In both cases the forecasts are done for 24 hours ahead.

Given the results, one could conclude that the above algorithm proposes a valuable asset for the energy producers. In particular, with the proposed model:

1. An energy producer can increase his profit, optimizing daily operations with the ability to see future. In the case of a hydro power plant (HPP) with reservoir, production (generation) decisions could be made under the light of these accurate forecasts. This case could be evaluated for two different conditions.
   a. A HPP owner with low capacity has to consider both prices and water inflow in order to maximize its profit. Numerous production operations are held throughout the day. Using the proposed forecasting tool, the most advantageous hours from price side could be determined to minimize loss. For instance, the power plant owner has to make a turbine operation between 2-5 pm in order to cause no loss due to waste of resource (water inflow in this case). Once the interval is determined, the next step is to decide the exact hour. The proposed tool can be utilized in order to mitigate risks in such a condition.

b. A HPP owner with high capacity does not have to worry about the inflow as long as the capacity has not reached the upper limit. Therefore, the turbines run with high efficiency most of the time, meaning that the only consideration is the price itself. With the tool we propose, HPP owner can make more accurate decisions during the bidding process and can have more balanced production as a consequence.

2. An investment decision can be evaluated considering the future of the market.
3. Players will make more stable decisions, and hence, the market would be more balanced.
4. As explained under market definition section, there are no time limitations for bilateral contracts between market players, even though the bidding process for day-ahead ends at 11.00 every day. Hence, there is an opportunity to buy and sell electricity for a week-ahead as well. With the SARIMA-ANN hybridization that is proposed in this paper, a market player can make more accurate and risk-free short-term hedging operations. The ability to see the future with less risk comes with increasing profit, using opportunities.

As clearly seen in Table II, MAPE for conventional SARIMA process was 5,03% and 13,8% for in-sample and out-of-sample testing. These error percentages were reduced to 4,08% and 10,2% after implementing ANN to forecast the residuals.

VI. CONCLUSION

Energy pricing in the spot market is highly important for the market players to have the day-ahead flexibility. However, when data is not transparent, fundamental methods proposed by the stationary markets are not applicable. This study proposes a new hybrid model for time series forecasting in such markets where data can be incomplete and highly dependent on the historical data.

The proposed model is composed of SARIMA and ANN with BP learning, where linear part of the data is the trend forecasted by SARIMA; and ANN forecasts the non-linear residuals. The results of both steps are combined for corrections. The model is applied in the Turkish electricity markets where liberalization is not yet completed. Data is received from the governmental authorities. Errors of forecasts are reduced almost 4%, indicating almost 30% improvement. Hybrid model is compared with the results of simple use of SARIMA and ANN; and the power of hybridization is shown.

It is recommended that the proposed method is applied in different markets and the results shall be compared. It will be a big leap to use adoptive methods in the proposed approach. Achievements of this study will lead for all the energy market role players in Turkey. Furthermore, energy investors in developing countries will have a great tool to look ahead more accurately.

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