Hybrid Approach of Additive and Multiplicative Decomposition Method for Electricity Price Forecasting

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Abstract: **The forecast of electricity price has become an important aspect of the electricity market due to competitive business environment. Power producers and consumers are bound to determine a precise price forecasting because this information is vital for decision making process and directly linked with company profit. Decisions, regarding optimal scheduling of generators, bidding strategies and demand side management are based on price forecast. In recent years, development of new approaches for short term price forecasting has captured the interest of the researchers. The electricity price forecasting is difficult due to its volatile nature. Moreover, the electricity can't be stock piled like other commodities. With these two issues, forecasting of electricity price has become a daunting task to perform for system planners and designers. This paper presents a comparative study of time series methods namely Decomposition, Moving Average and Trend analysis methods to forecast the electricity price. A meaningful comparison of forecasting results is presented on the basis of standard error indices.**

Key Words: **Historical data, Time series, Forecasting, Electricity price.**

1. INTRODUCTION

In recent years, price forecast has become a topic of interest in power system research due to deregulation of the electricity markets. Based on the duration, the price forecast can be divided into three categories. Forecast for a few days, a few months and a few years are classified as short term, medium term and long term respectively. The accuracy of the forecasting decreases as the time span increases. With the emerging technologies, different methods have been suggested for price forecasting. The price patterns are non-homogeneous and aperiodic. Issues related to volatility in fuel price, load uncertainty, transmission congestion can be considered as prime hurdles in price forecasting.

Short Term Price Forecasting (STPF) is considered as an essential exercise carried out by GENCOS in setting up the bidding strategies. There are various factors which contribute to the electricity price volatility; these factors are time, weather cycle, random disturbance and consumer's behavior. STPF of the electricity is also used for operational planning of power system at distribution and transmission level.

Accuracy of price forecasting method plays an important role. As, any error in the prediction of electricity price can cause huge amount of revenue loss in the system. Literature survey of references [1-16] shows that many researchers have put forward new supervised learning techniques. ANN [13], factorial design model [14], linear regression models [15], space state model [16], and a few regression models were opted in sequence to forecast the day-ahead electricity price.

In [1-2] authors proposed a method based on artificial neural network model. This method employed four-layered perceptron neural network to forecast the day-ahead price of electricity. Meta Heuristic Algorithm to train the feed forward Neural Network is employed in [3]. Modified Relief algorithm is employed with hybrid neural network by N. Amjady [4]. In [5] the author employed similar days method to forecast day ahead electricity price by assuming correlation between price and load. Weekly insert contrast data is used as insert factors of neural network in [6]. In [7] a state space model technique has been used for forecasting of electricity price.

Price point and interval of prediction of forecasting for price has been performed with functional principal component in reference [8]. Short term price forecasting with the help of the chaos theory was presented in [9]. To address the issues of the spiking nature and volatility in electricity price, authors in reference [10] introduced Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method to model the dynamic character of price. Fuzzy neural network system has been implemented by the author for price forecasting in [11]. The most useful feature of fuzzy logic is that it does not depend on modeling or mathematical relationship. Inclusion of error noise in the data series is not an important issue for prediction of the data with fuzzy logic approaches [12-13]. Pattern sequence similarity technique was proposed by the authors Francisco et.al [14]. Neural based approach has been implemented for forecasting the electricity price by the authors in references [15-16]. A state space model for forecasting was published by Yanxia-Lu et.al [17]. A hybrid approach of using Support Vector Machine (SVM) with linear regression for short term price forecasting (STPF) was proposed in [18].

After a critical investigation of the literature it can be concluded that supervised learning models namely Feed Forward Neural Network (FFNN), Radial Basis Function Neural Network (RBFNN), and SVM are the most useful regression techniques to forecast the electricity price. The performance of the neural networks is reasonably good due to its capability to deal with the mapping problems. However, computational time and determination of the suitable set of parameters for deciding the macro and mini structure of the neural network are some of the critical issues. This paper proposes a technique based on multiplicative additive decomposition method via time series modeling to predict electricity price. Following are the research objectives of the paper:

a. To cluster the data set on the basis of price hike, events and some declared holidays. To discover similar patterns for application of different time series modeling methods to forecast the data on hourly basis.
b. To present a comparison of different statistical approaches based on the prediction error indices and forecasted results.

The remaining part of the paper is organized as follows: Section 2 presents the time series model approach, section 3 and 4 explain the data analysis and section 5 and 6 present the simulation results and conclusion drawn respectively.

2. HISTORICAL DATA ANALYSIS:

For forecasting the electricity prices for a week of the year 2010, containing all 7 days (Monday-Sunday) a data series for the years 2006, 2007, 2008 and 2009 is analyzed. The data for the operation on the time series modeling is taken from Spain Electricity Market (Iberian Energy Derivation Exchange) [19].

Historical electricity price data need to be analyzed before moving forward to forecasting process. For the analysis of behavior of prices, electricity data of Spain Electricity Market is considered. The study of historical data shows the average price behavior for a particular day. Figures (1-3) show the behavior of price of electricity on Christmas, Independence and New Year Days over the past four years 2006, 2007, 2008, and 2009. On similar days' price follows a similar trend thus an optimal trend set is possible for forecasting by the proposed method.

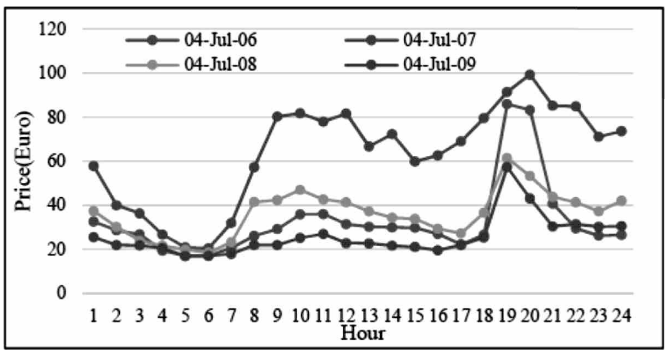

Fig.1 Electricity Price variation on 4th July (Independence Days) (2006-2009)

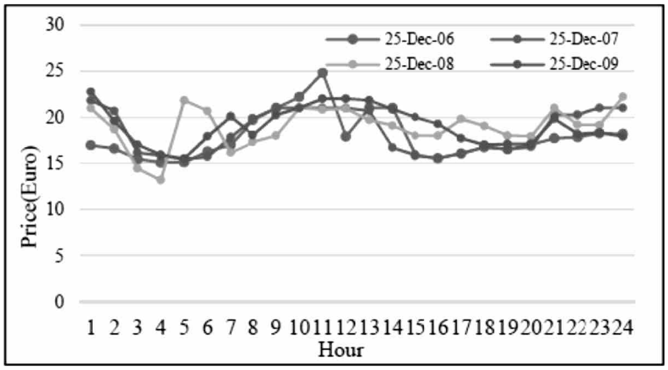

Fig. 2. Electricity Price variation on Christmas days (2006-2009)

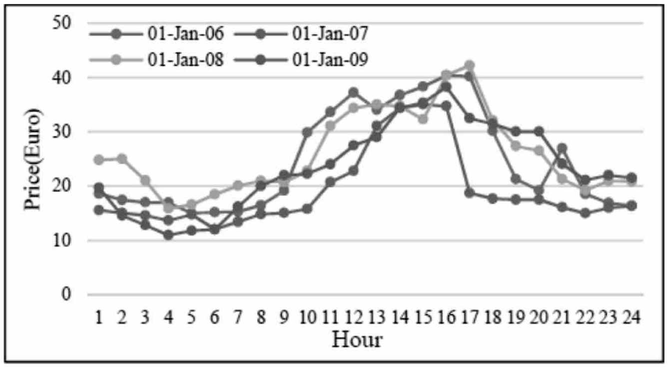

Fig. 3. Electricity Price variations on New Year's days(2006-2009)

Figure 4 shows the average values of the electricity prices taken over 52 Mondays, 52 Tuesdays, 52 Wednesdays, 52 Thursdays, 52 Fridays, and as a weekend off 52 Saturdays and 53 Sundays data for the year 2009.

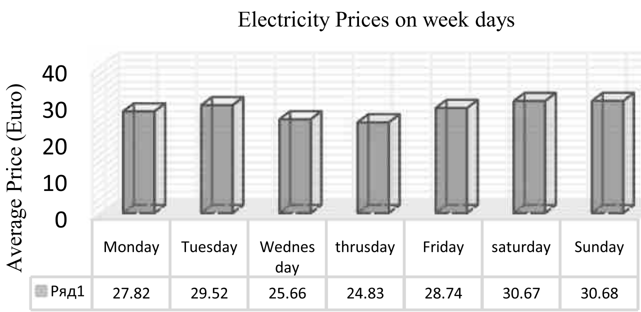

Fig. 4.Average Electricity price for a complete year 2009

The average price of electricity falls in a very narrow range. Hence, the applications of time series methods are suitable on this data.

3. METHODOLOGY :

For forecasting the electricity price on first Monday of the year 2010, i.e. 4 Jan 2010, we use the price data of all previous 52 Mondays [5 Jan 2006, 12 Jan 2006, --to-- 21 Dec, 28 Dec 2009] similarly the data is collected for Tuesdays to Sundays. It is observed that for special days like New Year, Christmas, Labor Day the behavior of price is more complex. For analyzing the trend of usage of electricity, we need to incorporate the trend of usage of electricity separately on working days, festive days and government declared holidays.

The Mean Absolute Percentage Error (MAPE), and the Mean Absolute Deviation (MAD), are defined below. These indices are used to exhibit the accuracy of this forecasting approach. MAPE may be easier to understand than other statistics due to its percentage in a direct number form. MAPE in mathematical form can be defined as:

$$\text{MAPE}=\frac{1}{N}\left|\frac{[Y_{act}\,(i)-Y_{pre}\,(i)]}{Y_{act}\,(i)}\right| * 100\% \qquad (1)$$

i = 1, 2, 3, 4.... N=Number of fitted points (24)

Where Y_{act} is the actual value of the electricity price and Y_{pre} is the predicted value of the electricity price

$$\text{MAD}=\frac{1}{N}\sum_{i=1}^{n}|x_i - m(x)| \qquad (2)$$

m(x)=forecast value

N = Number of fitted points

x_i = Actual Value

Value of m(x) has a marked effect on the mean deviation. The following section presents the results and critical evaluation of the findings.

4. TIME SERIES FORECASTING METHODS

Time series methods are employed to discover the pattern in historical data and to extrapolate this pattern in the future. The electricity price pattern behavior must be studied very carefully to find the forecast of future electricity price. There exists four-time series pattern behavior in the historical data such as trend, seasonal, cyclic pattern and irregular movement. A trend pattern exists in a data series when there is a long-term increase or decrease in the historical data. A seasonal pattern occurs when a data series is influenced by seasonal factors. A cyclic pattern occurs where the fluctuations are not of fixed period in the data series. The impact of random noise and error components in the data are considered as the irregular movement. The historical data of electricity price consists of these series patterns. The impact of components must be identified on the time series specially the noise component. Developing mathematical models for an observed time series and consequently using these models for forecasting is one of the most important applications of time series analysis. Time series forecasting is the prediction of future events based on already known past events using an appropriate model.

4.1 Trend Analysis:

Trend analysis is the most general approach based on exploring historical data to find trend to make forecasts. For better results, despite considering a particular day data, many similar days, data are fitted to explicate a specific trend. Least square method is used for trend projection which uses the data in the track for predictions by using fit trend equation. In trend analysis, a general trend model is fitted with the time series data. A particular trend model is selected from: linear, quadratic, exponential growth or decay, and S-curve trend models to fit trend. This procedure provides greater accuracy and efficiency when there is no seasonal component in the series. Equation 3 is used to calculate the average and to predict the next period set.

$$X_{t+1} = \frac{\sum_{t=1}^{n} X_t}{n} = \bar{X} \qquad (3)$$

Where X=Forecasted data, t=Time, X_t= Value of price at time t, n=total samples. The first n data points are used as the initialization part and rest as a test part. By default, it uses the linear trend model. If there is simple curvature in the data, the quadratic trend model is used. The exponential growth trend model is performed for exponential growth or decay. This accounts for the condition where the data series deals an S-shaped curve. In this work we used linear trend. because a trend pattern consists with historical data of electricity price.

4.2 Decomposition Method

To deal with dynamical system without linearization or weak non-linearity assumptions, closure estimates, perturbation theory or obstructive assumptions on stochasticitiy, decomposition method can be an effective approach. Decomposition separates the linear trend and seasonal components from the time series and computes the prediction as the linear regression line multiplied by (multiplicative model) or added to (additive model) the seasonal indices. On the basis of nature of seasonal component, additive and multiplicative models for decomposition is selected.

- **Additive model**

In this method the effects of different factors are separated and added together to model the data. The additive model is more suitable if the magnitude of the seasonal fluctuations around the trend-cycle does not vary much. Additive seasonal model assumes that time series can be defined as

$$P(t)=T(t)+S(t)+E(t) \qquad (4)$$

where P(t) is observation at time t, T(t) is the trend-cycle component, S(t) is the seasonal component at time t during the period considered, E(t) is for the remainder (or irregular or error) component period.

- **Multiplicative model**

In this model, the trend and seasonal components are multiplied. Data prior to the forecast origin are used for the decomposition. Multiplicative seasonal model assumes that time series can be defined as

$$P(t) = T(t) * S(t) * E(t) \qquad (5)$$

The individual cyclic component is not applicable to STLF due to its time duration period. With economic time series, multiplicative models are common and reliable. A substitute to using a multiplicative model, is to first transform the data until the dissimilarity in the series appears to be stable over time, and then use an additive model. A log transformation can be used, which is equivalent to using a multiplicative decomposition.

$$\text{Log}\, P(t) = \text{Log}\, T(t) + \text{Log}\, S(t) + \text{Log}\, E(t) \quad (6)$$

The trend of the time series in the electricity price data must be found and extended into the future in order to apply decomposition model. The equation of the trend line is generalized to estimate the trend in the past and future. Seasonal effects can be integrated into the future trend forecasts to account for the intra-day variation and obtain forecasts. Seasonal length is the length of seasonal component in the time series. For example, seasonal length should be 12 for monthly data and 7 for weekly data. Table 1 shows the different values of trend, seasonal, detrend and de seasonal values. From figure 5 it is observed that the data possess seasonal and nonlinear content. Seasonal indices are predictor of the comparison between any season and average season.

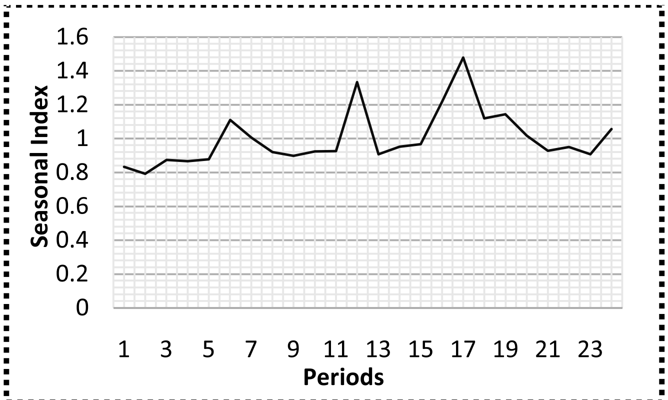

Fig.5 Seasonal index for first Monday 24 hours

TABLE 1.
Different Statistical Parameters For Decomposition Method

Mondays	Actual price (€) for 1st hour	Trend	Seasonal	Detrend	De seasonal	Predicted Value	% Error
1	24.18	25.879	0.83306	0.93435	29.0255	21.5588	2.6212
2	24.83	25.81	0.79138	0.96203	31.3754	20.4256	4.4044
3	25	25.7409	0.87294	0.97122	28.6387	22.4704	2.5296
4	25.88	25.6718	0.8665	1.00811	29.8673	22.2446	3.6354
5	21.17	25.6027	0.87782	0.82686	24.1166	22.4745	-1.3045
6	21.84	25.5337	1.10965	0.85534	19.6818	28.3335	-6.4935
7	19.52	25.4646	1.00481	0.76655	19.4265	25.5871	-6.0671
8	21.94	25.3955	0.91916	0.86393	23.8697	23.3425	-1.4025
9	20.41	25.3265	0.89795	0.80588	22.7296	22.7419	2.3319
10	18.59	25.2574	0.92431	0.73602	20.1124	23.3456	-4.7556
11	22	25.1883	0.92569	0.87342	23.7661	23.3166	-1.3166
12	22	25.1193	1.33366	0.87582	16.496	33.5005	-11.505
13	22.17	25.0502	0.90706	0.88502	24.4415	22.7221	-0.5521
14	24.86	24.9811	0.95204	0.99515	26.1122	23.7831	1.0769
15	25.29	24.9121	0.96611	1.01517	26.1772	24.0677	1.2223
16	37.86	24.843	1.21798	1.52397	31.0841	30.2584	7.6016
17	37.41	24.7739	1.4787	1.51006	25.2993	36.6331	0.7769
18	28.45	24.7049	1.11862	1.1516	25.4332	27.6353	0.8147
19	29.35	24.6358	1.14411	1.19136	25.6532	28.186	1.164
20	26.21	24.5667	1.01753	1.06689	25.7584	24.9974	1.2126
21	23.92	24.4976	0.92782	0.97642	25.7808	22.7295	1.1905
22	24.59	24.4286	0.95041	1.00661	25.873	23.2172	1.3728
23	23.53	24.3595	0.90707	0.96595	25.9407	22.0957	1.4343
24	27.59	24.2904	1.05562	1.13584	26.1364	25.6414	1.9486
25	21.94	24.2214	0.83306	0.90581	26.3366	20.1779	1.7621
26	20.79	24.1523	0.79138	0.86079	26.2705	19.1137	1.6763
27	22.81	24.0832	0.87294	0.94713	26.1299	21.0233	1.7867
28	22.28	24.0142	0.8665	0.92779	25.7127	20.8082	1.4718
29	21.98	23.9451	0.87782	0.91793	25.0394	21.0194	0.9606
30	27.24	23.876	1.10965	1.14089	24.5482	26.4941	0.7459
31	24.33	23.807	1.00481	1.02197	24.2135	23.9215	0.4085
32	22.01	23.7379	0.91916	0.92721	23.9458	21.8189	0.1911
33	21.38	23.6688	0.89795	0.9033	23.8098	21.2534	0.1266
34	21.9	23.5998	0.92431	0.92798	23.6934	21.8134	0.0866
35	21.83	23.5307	0.92569	0.92772	23.5824	21.7821	0.0479
36	31.25	23.4616	1.33366	1.33196	23.4318	31.2898	-0.0398
37	22.21	23.3925	0.90706	0.94945	24.4856	21.2185	0.9915
38	21.75	23.3235	0.95204	0.93254	22.8456	22.205	-0.455
39	21.88	23.2544	0.96611	0.9409	22.6476	22.4662	-0.5862
40	21.91	23.1853	1.21798	0.94499	17.9887	28.2394	-6.3294
41	22.12	23.1163	1.4787	0.9569	14.9591	34.182	-12.062
42	20.95	23.0472	1.11862	0.909	18.7285	25.781	-4.831
43	21.32	22.9781	1.14411	0.92784	18.6346	26.2894	-4.9694
44	21.82	22.9091	1.01753	0.95246	21.444	23.3107	-1.4907
45	22	22.84	0.92782	0.96322	23.7114	21.1915	0.8085
46	21.11	22.7709	0.95041	0.92706	22.2115	21.6417	-0.5317
47	21.86	22.7019	0.90707	0.96292	24.0996	20.5921	1.2679
48	22.27	22.6328	1.05562	0.98397	21.0967	23.8915	-1.6215
49	21.07	22.5637	0.83306	0.9338	25.2923	18.7969	2.2731
50	21.48	22.4947	0.79138	0.95489	27.1424	17.8019	3.6781
51	21.48	22.4256	0.87294	0.95783	24.6064	19.5763	1.9037
52	21.42	22.3565	0.8665	0.95811	24.7202	19.3719	2.0481

4.3 Moving Average Method

Moving average method is used for smoothing the data by averaging consecutive observations in a series. It also highlights the long-term trends or cycles. Moving average method is performed on the data which do not have the trend and seasonal component. The moving average length which is selected for the moving average method may depend on the amount of noise present in the data series. With non-seasonal time series, it is normal to use short moving averages to make the series smooth. A longer moving average filters out more noise, but makes it less sensitive to fluctuations in the series.

With seasonal series, it is optimal to use a moving average of length equal to the length of a yearly cycle. Linear moving average method can be used by performing successive moving averages. This is usually done when there is a trend in the data. Equations 7 and 8are used to calculate the moving average.

$$Movingaverage\ (P_t) = \frac{\sum Price\ in\ previous\ years}{N} \quad (7)$$

$$(P_t) = \frac{\sum_{i=1}^{n} p(t-i)}{N} \quad (8)$$

N = Number of Periods

Where N is the number of periods in the moving average. Center Moving Average (CMA) is calculated to position the moving average values at their central positions in time. In center moving average the value of the moving average is shifted at the period which is in the center of the series rather than at the end of the series. There are three major types of moving average i.e. Simple Moving Average (SMA), Exponential Moving Average (EMA) and Weighted Moving Average (WMA).

In this paper, we have chosen 24 moving averages and stacked the hourly data of week days and weekends for the years 2006 to 2009 for the prediction of electricity price for the year 2010. Table 2 represents the lower and upper limit of the forecasting result on the basis of moving average length (24).

TABLE 2.
Moving Average Lower Upper Limit Values

Hour	Lower Price (€)	Forecast Price (€)	Upper Price (€)
0	21.583	13.1217	30.0433
1	21.181	15.9496	26.4124
2	19.133	19.8902	24.3758
3	18.439	11.8701	25.0079
4	18.27	10.5101	26.0299
5	20.252	15.1642	25.3398
6	24.234	10.2637	38.2043
7	24.22	0.26171	48.1783
8	25.544	-2.84194	53.9299
9	29.786	7.45016	52.1218
10	33.818	12.5434	55.0926
11	33.615	14.7103	52.5287
12	38.247	15.6779	60.8161
13	45.437	14.68	76.1876
14	46.685	13.8897	79.8403
15	40.331	10.0685	70.5935
16	50.065	17.4005	82.7295
17	40.319	17.0527	63.5873
18	31.97	-7.145	71.0646
19	29.534	-7.42938	66.1374
20	29.63	13.7803	45.4797
21	24.395	10.1476	38.6424
22	22.809	15.6261	29.9919
23	22.252	14.304	30.2

5. RESULTS

This section presents the prediction of electric price by trend analysis, decomposition and moving average methods for the first week of January, 2010 of Spain Electricity Market. Minitab software package is employed to perform this forecasting. 52 weeks data of hourly electricity price of previous years (2006-

2009) is compiled in order to forecast the hourly price of the first week of the year 2010. Table 3 shows forecasted price data for Saturdays and Sundays of first week of the year 2010. Figures 6-8 show the forecasted results obtained from all three methods. To draw a comparison of the prediction performance by these methods, Mean Average Percentage Error (MAPE), Mean Absolute Deviation (MAD) error indices are calculated for these models. These indices are shown in figures 9-11. Figure 6 shows the price forecast for the first Sunday of the year 2010. All the three methods predicted price hike in 21st hour, which matches with the available actual price.

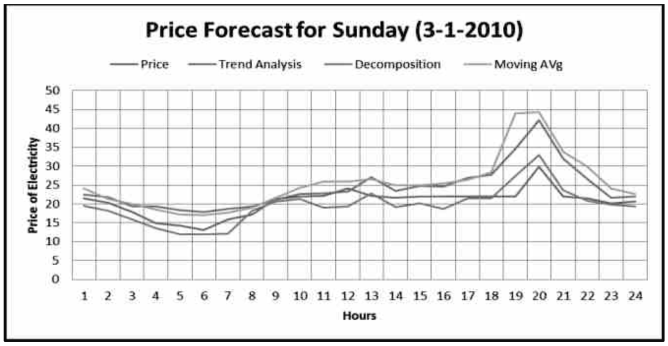

Fig.6. Price forecasting for first Sunday of the year 2010

Figures 7and 8 show the price forecast for Saturday (2 January 2010) and Tuesday (5 January 2010) respectively and it is observed that numerical values of error indices are comparatively higher for Saturday and Tuesday for all methods. These results are plotted in figures 9 to 11.

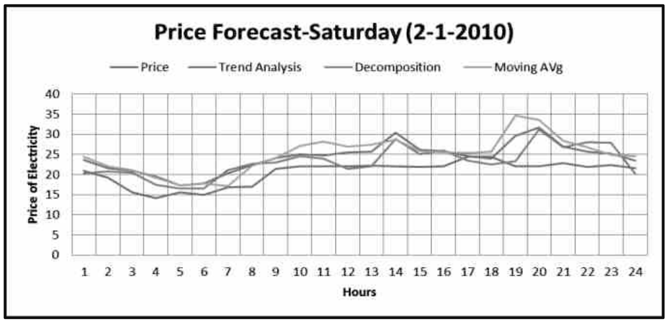

Fig.7. Price forecasting for first Saturday of the year 2010

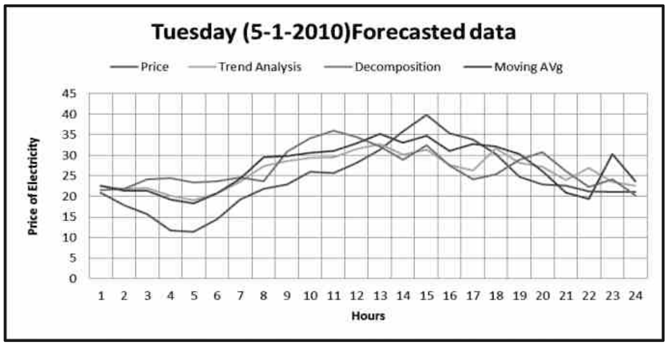

Fig.8. Price forecasting for first Tuesday of the year 2010

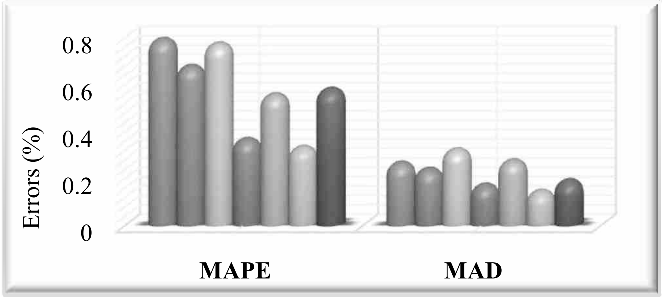

Fig.9. Comparative results of Errors on week days of 2010 for Trend Analysis method

Figure 9 shows the comparison of different indices for weekdays of January 2010. It is again observed that the values of error indices are more for Monday to Wednesday.

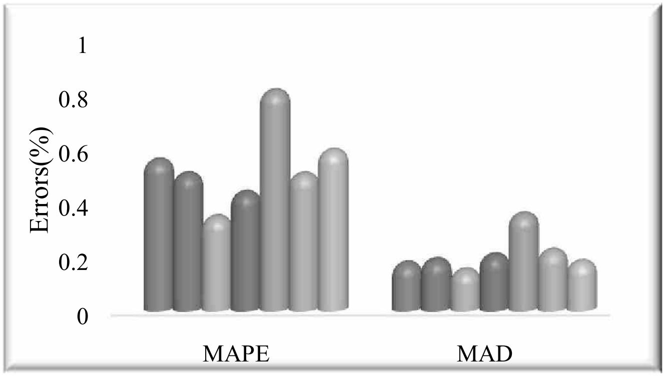

Fig. 10. Comparative results of Errors on week days of 2010 for Moving Average method

Figures 10 and 11 show the error indices for the Moving average and decomposition methods respectively. From figure 11 it can be observed that the highest numerical values of these indices are observed for Wednesday.

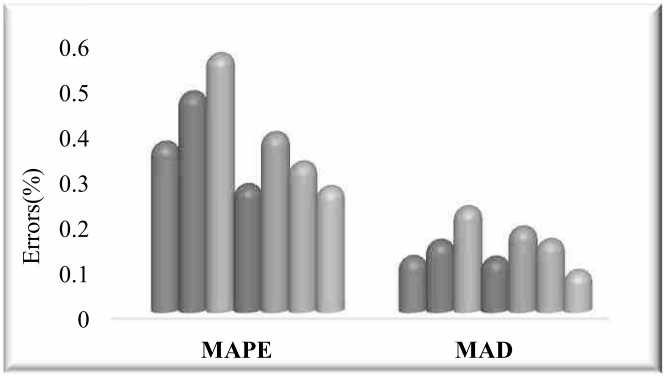

Fig. 11. Comparative results of Errors on week days of 2010 for Decomposition method

Similarly, with trend analysis method highest error is observed with first three weekdays.

TABLE 3.
Forecasted Values Of Hourly Price (€) From Different Methods For Weekend

Hours	Saturday				Sunday			
	Actual	Trend Analysis	Decomposition	Moving Average	Actual	Trend Analysis	Decomposition	Moving Average
1	21	23.61	20.33	24.45	21.4	22.45	19.42	24.15
2	19.27	21.51	20.72	22.09	20.33	21.71	18.24	21.37
3	15.63	21.02	20.42	21.06	17.89	19.36	15.57	20.04
4	14.08	19.52	17.56	19.23	14.91	19.83	13.54	18.43
5	15.56	17.37	16.56	17.33	14.18	18.38	11.9	17.17
6	14.87	17.78	16.54	17.72	13.13	17.92	11.87	16.98
7	16.86	20.25	21.05	17.1	15.92	18.68	12.1	17.66
8	17.07	22.36	22.69	22.23	17.27	19.32	18.11	18.95
9	21.04	24.06	23.03	24.17	21.23	21.16	20.63	21.6
10	22.01	25.11	24.65	27.13	22.01	22.61	21.29	24.27
11	22.11	24.79	23.99	28.23	22.17	22.73	19.2	25.93
12	22.07	25.51	21.41	26.88	24.13	23.43	19.34	25.63
13	22.13	25.7	22.01	27.43	22.07	26.97	22.76	26.59
14	22	30.47	22.01	28.73	21.58	23.49	19.18	24.9
15	21.83	26.16	25.05	25.81	22	24.78	20.11	24.95
16	22	25.87	25.97	25.45	22	24.64	18.7	25.36
17	24.39	24.63	23.45	25.33	21.99	26.97	21.05	26.36
18	24.41	23.87	22.58	25.75	21.96	27.75	21.53	28.44
19	22.01	29.68	23.37	34.62	22.02	34.64	27.53	23.95
20	21.98	31.7	31.25	33.59	29.81	32.19	33.02	34.56
21	22.83	26.97	26.85	28.32	22	32.03	23.53	33.79
22	21.96	25.67	28.11	26.85	21.53	26.58	20.83	29.88
23	22.4	25.28	27.84	24.83	20.15	21.53	19.8	24.07
24	21.6	23.4	20.22	24.62	20.61	21.93	19.3	22.7

The following points emerge from Table 3.

a. Electricity price forecast for Saturday fall in a narrow range by all three methods. Highest variations in electricity price are observed during 21st hour. Average values of electricity price for this day comes out as 24.2608, 22.81 and 24.95 Euros from trend analysis, decomposition and moving average methods respectively. Actual average price for this particular day is 20.46 Euros. From here, we can observe that price prediction by decomposition method is more near to actual value as compared with other methods.

b. Electricity price forecast for Sunday is shown in Table 3. It is observed that the average values of electricity price forecasted by all three methods are 23.79, 19.52 and 24.07Euros. The actual price on this particular day is 20.51 Euros. Again, it is observed that decomposition method predicts electricity price closer to actual value as compared with other two methods.

c. Values of standard deviations in prediction are as follows For Monday and Wednesday moving average method results in higher values of standard deviation that are 0.6 and 0.8 respectively, whereas for trend analysis these values are 0.8 and 0.79 respectively. However, for decomposition method these values are as low as 0.4 and 0.55. The values of standard deviations of actual price are also very close to values predicted by decomposition method.

TABLE 4.
Forecasted Values Of Hourly Price (€) From Different Methods For Working Days

Hours	Tuesday				Wednesday			
	Actual	Trend Analysis	Decomposition	Moving Average	Actual	Trend Analysis	Decomposition	Moving Average
1	20.96	22.44	21.55	22.55	20.83	21.99	19.58	22.04
2	17.84	21.81	21.87	21.36	16.87	21.47	18.77	21.39
3	15.69	21.94	24.14	21.31	14.66	20.57	17.91	20.52
4	11.76	20.17	24.52	19.19	12.01	19.47	16.21	18.58
5	11.4	19.11	23.42	18.25	12.04	17.98	11.23	18.36
6	14.4	20.76	23.63	20.36	14.91	19.76	19.6	18.52
7	19.17	23.48	24.52	24.53	19.64	23.07	25.65	25.89
8	21.9	27.43	23.7	29.6	21.99	17.81	28.56	26.07
9	22.85	28.65	30.94	29.36	22.47	18.28	28.65	27.06
10	25.95	29.36	34.11	30.61	23.74	19.76	28.24	27.52
11	25.69	29.5	36.23	31.1	27.92	21.17	30.23	26.95
12	28.11	31.58	34.46	32.92	30.17	19.48	30.25	25.75
13	31.4	32.7	32.02	35.14	32.78	21.45	31.76	27.21
14	35.79	30.11	28.36	32.95	34.68	28.44	36.53	32.56
15	39.9	31.41	32.39	34.82	37.53	31.03	36.25	32.45
16	35.43	27.67	27.19	31.08	37.35	25.6	34.15	37.32
17	33.81	2623	24.18	32.08	37.73	34.34	38.23	36.17
18	30.29	31.07	25.39	32.14	30.95	25.33	31.66	32.14
19	24.76	28.06	28.97	30.23	25.16	24.03	31.03	36.12
20	22.96	27.82	30.69	26.14	22.79	28.18	35.25	29.2
21	22.62	24.04	26.12	20.94	22.33	19.49	29.56	24.86
22	21.26	26.89	22.32	19.43	21.32	18.25	25.62	22.31
23	21.09	23.56	24.18	30.23	21.7	22.77	20.95	18.4
24	21.14	22.56	20.23	23.65	22	22.52	25.63	22.13

In a similar manner, price forecasts for Tuesdays and Wednesdays are shown in Table 4. On observations, it can be concluded that the decomposition method gives better accuracy as the average values of predicted price for 24 hours on both days fall very close to actual values. The standard deviation calculations of the predicted values are very low.

With these observations, it can be concluded that lowest prediction error is for Tuesdays and Wednesday. Following section presents the conclusion and highlights of this work.

6. CONCLUSION

In the competitive market scenario, precise forecast of electricity price is inevitable. Due to its responsible denominating ability for planning and close correlation between power producers and the consumer a method for short-term price forecasting is presented which is needed for important decision making and bidding strategies. In this three different techniques have been employed namely Trend Analysis, Decomposition and Moving Average to forecast the electricity price. These models have been tested on Spain Electricity Market data and a comparative analysis of these results has been exhibited in the paper.

Following are the major contributions of this research work.

1. Forecast of the electricity price for first week of January 2010 based on three different models is carried out with the help of historical data sets for years from 2006 to 2009.
2. A comparison on the basis of forecasting error indices namely MAPE and MAD has been derived and it is concluded that Decomposition method possesses better accuracy as compared to Trend analysis and Moving Average techniques.
3. The application of different hybrid models with the incorporation of neural networks and analytical time series lays in the future scope of this work.

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