Stochastic Modelling Compared With Artificial Intelligence Based Approach For Electrical Load Forecasting

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Abstract: Accurate load forecasting is very important for electric utilities in planning for new plants. Also it is very significant for the routine of maintaining, scheduling daily, electrical generation, and loads. In this study, emphasis was considered on short-term load forecasting which is important for real time operation and control of power systems. Artificial intelligence and stochastic forecasting models were examined. The performance of these models is dependent on the characteristics of electric loads and is based on the assumption that electric load patterns are basically invariant with time. Two different models were considered and a new stochastic model (called REGARIMA) was introduced and compared with ANFIS model. Both models were tested and shown to be the best one that represents the available data. The results obtained using the two approaches are very accurate and mutually competitive. Furthermore, they are very promising in short term forecasting techniques, which could be applied as well on wind speed forecasting.

1. Introduction

Electrical load forecasting plays a central role in the operation and planning of power systems. The country wide energy estimation, the planning of new plants, the routine maintaining and scheduling of daily electric generation are dependent on accurate load forecasting. In this research Short Term Load Forecasting (STLF) will be considered. One of the most important benefits of the STLF is reliability for the power system i.e. to make these investments reliable via optimal accurate load forecasting. Short-term load forecasting is a very important task for electric utilities in order to manage the production, transmission, and distribution as well as generation of electricity in a more efficient and secure way. As an example of the importance of accurate forecasts, it was estimated that an increase of only 1% in the forecast error (in 1984) caused an increase of 10 million pounds in operating costs per year for one electric utility in the United Kingdom [1]. The first step in load forecasting is to collect the historical data of the system to be studied. This data could be the daily peak load (according to the type of forecasting to be operated), and always construct a time series y_t. Where y_t is the electric load as a function of time. There are many factors that affect the electric load demand like time variation, gross national product, population, and climatic changes. And the more we are precise in determining their effect on load

demand the more accurate forecasting we get. The main mission for a forecaster is to study the behaviour of the collected historical data (which is called data mining), and determining the different patterns of the time series [2].

This work studies the applicability of two different models on short-term load forecasting. The approach is comparative. The models are: Time Series model and Artificial Intelligent model to forecasting the daily peak load. Testing is carried out on the real load data of a North Cairo electric utility. The objective is to accomplish suggestions on choosing the most appropriate model(s).

As there is need to forecast the load accurately, another goal is to study the performance of the models for different lead-times. Naturally, it seems possible that different models should be preferred for the short-term forecasting range. There are some properties, which are considered important:

- The model should be automatic and able to adapt quickly to changes in the load behaviour.
- The model is intended for use in many different cases. This means that generality is desired.
- Updating the forecast with new available data should be possible. The hours closest to the forecasting time should always be forecast as accurately as possible.

- The model should be reliable. Even exceptional circumstances must not give rise to unreasonable forecasts.
- The model should be easily attachable to an energy management system.

The proposed work does not study the forecasting for special days, such as religious and legal holidays. Special days have different consumption profiles from ordinary days, which make forecasting very difficult for them. Choosing a forecasting technique to be used in establishing future load requirements is a nontrivial task in itself. Depending on the nature of load variations, one particular method may be superior to another. Before choosing a particular method, whether it be simple curve fitting or stochastic modelling, a basic understanding of how a load behaves is essential. If, on the basis of historical data and good judgment, simple extrapolation appears to suffice, it should be used, unfortunately. This is due to all electric utilities are somewhat different. It is impossible to list all system attributes that may be adequately modelled by a particular technique. Choosing the best technique for a given utility, once again, requires good judgment and knowledge of the advantages and disadvantages of various available methods. Once a method has been chosen, the forecaster must always re-evaluate its effectiveness, because forecasting techniques can survive their usefulness, as a result of either drastic changes in a system or improvements in available methods [3].

A wide variety of models, varying in the complexity of functional form and estimation procedures, has been proposed for the improvement of load forecasting accuracy. Load forecasting techniques are classified into some categories. These categories of load forecasting techniques are [35]:

- Multiple regression [4, 7-9];
- Iterative reweighed least-squares [10] ;
- Adaptive load forecasting [11];
- Stochastic Modelling [12-17];
- Neural Networks [23-26];
- Fuzzy Logic [29]; and
- Neuro Fuzzy systems [32-34].

A large variety of mathematical methods and ideas have been used for load forecasting. The development and improvements of appropriate mathematical tools will lead to the development of more accurate load forecasting techniques. These categories of load forecasting techniques were discussed in [35].

The widely statistical measures of error that can help to identify method or the optimum value of the parameter within a method are:

i) Mean Absolute Error (MAE):

The mean absolute error Value is the average absolute error value. Closer this value is to zero the better is the forecast.

ii) Mean Squared Error (MSE):

Mean squared error is computed as the sum (or average) of the squared error values. This is the most commonly used lack-of-fit indicator in statistical fitting procedures. As compared to the mean absolute error value, this measure is very sensitive to any outlier; that is unique or rare large error values will impact greatly MSE value.

iii) Root Mean Squared Error (RMSE):

It displays the root mean square error for each model selected.

2. Characteristics of Peak Load Data:

Daily Peak Loads are used for short term load forecasting (STLF), and the notable features of this data type are:
a) The available data are the daily peak load in MW from north Cairo of Electricity Distribution Company for the years 2008 and 2009.
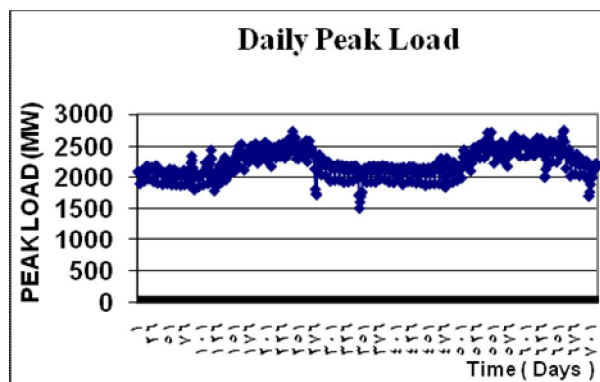b) The original data takes the shape illustrated in Figure 1.

Figure 1: Daily Peak Loads of the North Cairo UN

3. Results of Tested Models:

Time series analysis and forecasting is an active research area over the last few decades. The accuracy of time series forecasting is fundamental to many decision processes and hence the research for improving the effectiveness of forecasting models has never stopped. With the efforts of Box and Jenkins [12], The ARIMA model has become one of the most popular methods in the forecasting research and practice. More recently, artificial neural networks have shown their promise in time series forecasting applications with their nonlinear

modelling capability. Although both REGRESSION and ARIMA have the flexibility in modelling a variety of problems, none of them is the universal best model that can be used indiscriminately in every forecasting situation. The combination method can be an effective way to improve forecasting performance.

Different models were tested and investigated in this study. Among these models : two stochastic models were considered then compared to some ANFIS Models. The results will be illustrated and discussed as follow:

A) The Time Series Results:

In this study, a combined approach (Regression and ARIMA models) is implemented via the SAS software package [36]. The R-square value (Rsq), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Percentage Error (MPE) are selected to be the forecasting accuracy measures.

B) Multiple Regression Model:

The Multiple Regression method is applied on the historical data of the electric load consumption for 716 data points representing daily peak load for the years 2008 and 2009 in North Cairo. The SAS program is used to forecast the electrical load. Two Multiple Regression models are used:

- Multiple Regression for (t power 5);
- Multiple Regressions for (t power 12).

The resulting forecasts from the multiple regression model (REG^5) are shown in Figure 2. Also, the upper and lower 95% confidence limits of the forecasts are plotted. The estimated model parameters are given on the graph of Figure 2.
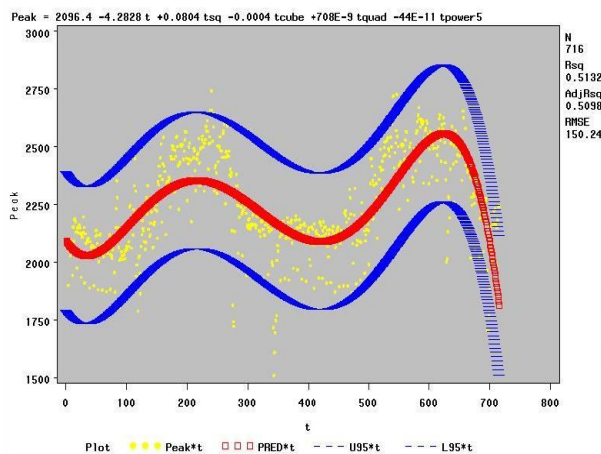

Figure 2 : Prediction of the Regression Model (t^5)

So the resulting equation of the 5th order Regression model is:

$P_{REG^5} = 2096.42422 - 4.28275t + 0.08043tsq - 0.00038745tcube + 7.07553E-7\ tquad - 4.3677\ E-10\ tpower5$ (1)

Where:

P_{REG^5} The predicted load for Regression model "t power 5", and

t is the time.

The residuals (or the errors) represent the difference between the original values of the load and the predicted values, based on the multiple regression model (REG^5), are shown in Figure 3. It should be noted that those errors are completely random and have a near-zero mean.
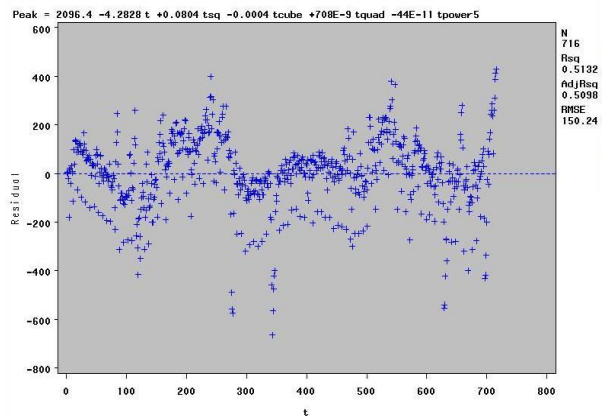

Figure 3 : Residuals of the Regression Model (t^5)

While the resulting forecast from the multiple regression model (REG^12) are shown in Figure 4. Also, the upper and lower 95% confidence limits of the forecasts are plotted. A Regression model of order 12 has been found to be the most accurate among all Regression models that were also found adequate as judged by the residual analysis.

After building the Regression model for (t power 12). It is found that the coefficient estimates of the model are shown on the graph illustrated in Figure 4.

So the resulting equation of the Regression model is:

$P_{REG^{12}} = 1969.20847 + 17.18128\ t - 0.60363\ tsq + 0.00807\ tcube - 0.00005172\ tquad + 1.815585E - 7\ tpower5 - 3.6612E-10\ tpower6 + 4.10676E - 13tpower7 - 2.1072E-16tpower8 + 2.80029E - 23tpower10 - 2.203325E-30tpower12$ (2)

Where:

$P_{REG^{12}}$ the predicted load for Regression model "t power 12", and

t is the time.

Also, the residuals or the error represent the difference between the original values of the load and the predicted values, based on the Regression model for (t power 12), are shown in Figure 5.

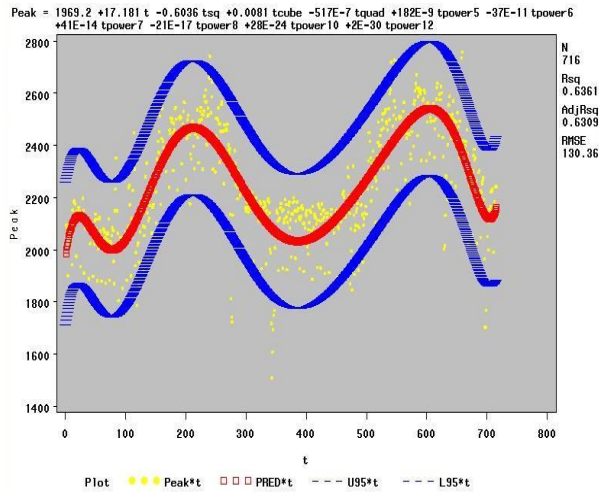Hence, as the root mean square of the residuals decreases the model will be more accurate.

Figure 4 : Prediction of the Regression Model (t^12)
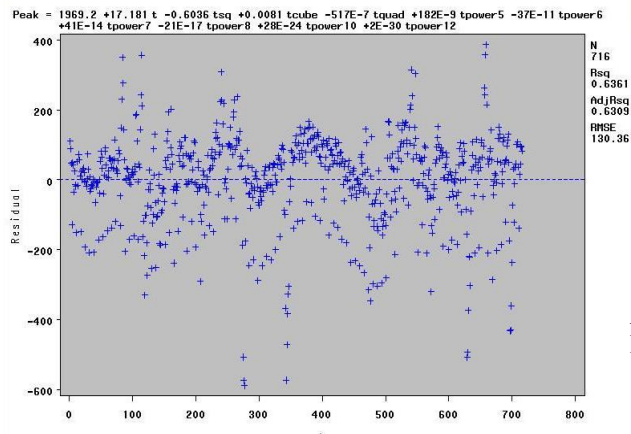

Figure 5 : Residuals of the Regression Model (t^12)

- The following descriptive statistics in Table (1) can distinguish the two models, showing Rsq, and RMSE.
- Different models, other than PREG^5 and, PREG^12, were also tested. The best results ere obtained with the PREG^12 model.

Table (1) : Regression Models Statistics

Model	Rsq	RMSE
P_{REG^5}	0.5132	150.24
$P_{REG^{12}}$	0.6361	130.36

From the above results, it is cleared that, the RMSE of $P_{REG^{12}}$ model is Less than the RMSE of P_{REG^5} model. On the contrary, the Rsq coefficient for $P_{REG^{12}}$ model is greater than the Rsq coefficient for P_{REG^5} model. Thus, the $P_{REG^{12}}$ model is more accurate.

C) ARIMA Model:

In this model, the residuals of the fitted Regression model ($P_{RESID.}$) were taken as the input data used for building the ARIMA model. Now, two models of ARIMA were built to get the best and accurate model forecast using SAS Package.

i) ARIMA model (1, 0, 1):
In this Model the coefficients are identified as: p=1, d=0, and q=1. Figure 6 presents the Autocorrelations of ARIMA (1, 0, 1) Model.
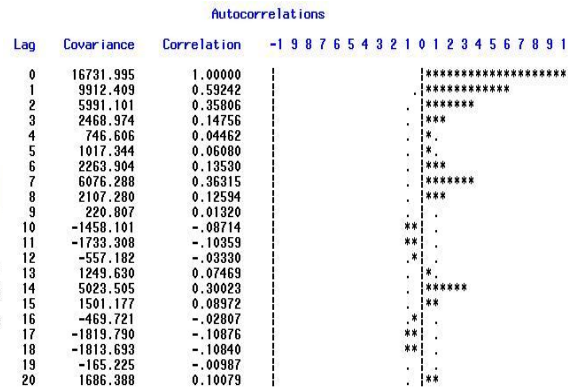

Figure 6 : Autocorrelations of ARIMA (1, 0, 1) Model

And the partial Autocorrelation of the ARIMA (1,0,1) Model as shown in Figures (5-7).
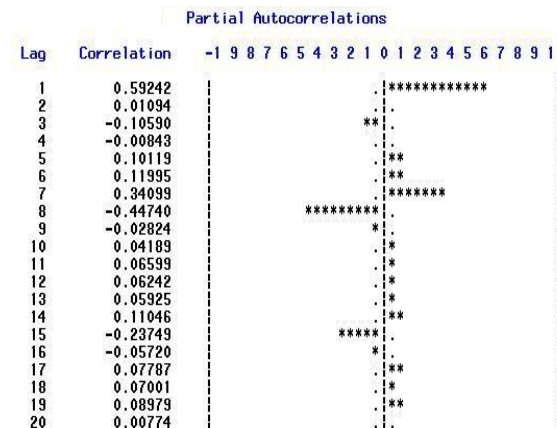

Figure 7 : Partial Autocorrelations of ARIMA (1, 0, 1) Model

The comparison of Figures 6, and 7 suggests that a differencing of degree 1 should be applied to the P_{RESID} data. Table (2) illustrates the electrical load forecasting of a combined REG^12 and ARIMA (1, 0, 1) models. The error presenting the difference between the original values of the load and the forecasted values, and the percentage error are given in Table (2). Hence, The Maximum Absolute Percentage Error is 8.11, which implies that the ARIMA (1, 0, 1) model has poor turning point forecasting ability.

ii)   ARIMA model (0, 1, 1):

In this Model the coefficients are p=0, d=1, and q=1. The Autocorrelations of the first differences of P_{RESID} are illustrated in Figure 8, and the partial Autocorrelation of the first differences of P_{RESID} are shown in Figure 9.

Table (2) : Combined of REG^12 and ARIMA (1, 0, 1) Models

Obs.	REG	ARIMA (1,0,1)	FORECAST	Measured	% Abs. Error
706	2,121.00	21.19	2,142.19	2,166.00	1.10
707	2,121.00	27.31	2,148.31	2,223.00	3.36
708	2,123.00	60.41	2,183.41	2,225.00	1.87
709	2,125.00	61.21	2,186.21	2,233.00	2.10
710	2,128.00	64.71	2,192.71	2,164.00	1.33
711	2,131.00	22.60	2,153.60	1,992.00	8.11
712	2,135.00	-81.10	2,053.90	2,151.00	4.51
713	2,140.00	8.51	2,148.51	2,184.00	1.62
714	2,146.00	26.29	2,172.29	2,241.00	3.07
715	2,152.00	56.72	2,208.72	2,245.00	1.62
716	2,159.00	55.69	2,214.69	2,242.00	1.22

Table (3) illustrates the electrical load forecasting of the combined REG^12 and ARIMA (0, 1, 1) model. This model will be called (REGARIMA), since it is based on combination of Regression model as well as ARIMA. The error represents the difference between the original values of the load and the forecasted values; and, it indicates as seen in Table (3), The Maximum Absolute Percentage Error is 2.98 %. So it indicates that the accuracy of ARIMA (0, 1, 1) is better than the previous model.

iii)   Choice of the Best Stochastic Model:

Table (4) shows that the ARIMA (0, 1, 1) model has the lower Root Mean Square Error (RMSE), lower Mean Absolute Error (MAE), and lower Mean Percentage

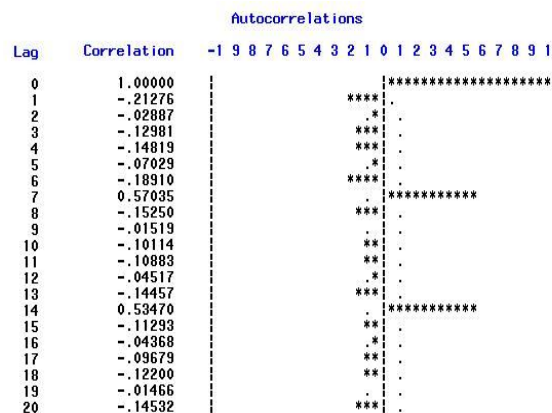Error (MPE), thus it is the best and accurate model for these data.

Figure 8 : Autocorrelations of ARIMA (0, 1, 1) Model
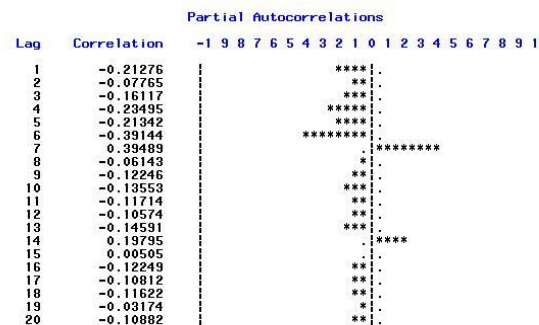
Figure 9 : Partial Autocorrelations of ARIMA (0, 1, 1) Model

Table (3) : Combined REG^12 and ARIMA (0, 1, 1) Models

Obs.	REG	ARIMA (0,1,1)	FORECAST REGARIMA	Measured	% Abs. Error
706	2,121.00	14.11	2,135.11	2,166.00	1.43
707	2,121.00	35.93	2,156.93	2,223.00	2.97
708	2,123.00	81.67	2,204.67	2,225.00	0.91
709	2,125.00	95.94	2,220.94	2,233.00	0.54
710	2,128.00	104.41	2,185.02	2,164.00	0.97
711	2,131.00	57.02	2,051.44	1,992.00	2.98
712	2,135.00	-79.56	2,121.92	2,151.00	1.35
713	2,140.00	-13.08	2,166.69	2,184.00	0.79
714	2,146.00	26.69	2,220.52	2,241.00	0.91
715	2,152.00	74.52	2,239.29	2,245.00	0.25
716	2,159.00	87.29	2,246.29	2,242.00	0.19

Table (4) : The Comparison of Two Different Stochastic Models

Model	RMSE	MAE	MPE
ARIMA (1, 0, 1)	70.37	23.77	1.00
ARIMA (0, 1, 1)	32.29	10.65	0. 46

D) ANFIS Model:

The ANFIS Model is applied on the historical data of the electric load consumption. Four different ANFIS Models were tested (using MATLAB and Simulink package [30]) to predict the best and accurate model. The inputs of the ANFIS system are considered the data of previous day to the forecasted day (Its Peak load).

    i)   Training data for ANFIS Model:

The training data used to train the ANFIS of the electrical load consumption are taken from 705 data point represents actual values of daily peak load for the years of 2008 and 2009 in North Cairo. It is the same data as used before.

    ii)   The ANFIS predictor:

The ANFIS predictor consists of Number of neurons in the input layer, three triangular Membership Functions (MF) for each input i.e. M=3 and constant membership function for the output. These types of MFs are chosen because they offer the best performance among other types of the MFs.

    iii)   Testing data for Model:

The used data were tested on the obtained ANFIS Model. After testing data the estimated values show promising models. So, the estimated values from the simulation model will be compared with the actual values to obtain the absolute error and the percentage error. However, these procedure will be repeated for four different ANFIS model (where the number of inputs are different in each case).

    iv)   Choice of The Best ANFIS Model:

The forecasted loads which obtained from the four Models of ANFIS demonstrate a good performance for ANFIS Model (2) which depends on (4 previous readings) as shown in Table (5). The choice of the best ANFIS Model depends on many coefficients such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Percentage Error (MPE). They are shown in Table (6), which shows that the best and

accurate model is ANFIS Model (2) which has the latest RMSE, MAE and MPE, so it is a very accurate model.

Table (5) : Comparison of Estimated Values of ANFIS Models

Measured	FORECAST			
	ANFIS Model (1)	ANFIS Model (2)	ANFIS Model (3)	ANFIS Model (4)
2166	2146	2167	2173	2128
2223	2155	2155	2115	2126
2225	2254	2212	2165	2190
2233	2160	2172	2172	2187
2164	2181	2180	2176	2197
1992	2012	2042	2079	2129
2151	2031	2076	2093	2056
2184	2127	2126	2129	2157
2241	2224	2211	2197	2149
2245	2227	2241	2194	2203
2242	2253	2201	2196	2216

Table (6) : Comparison of The Coefficients of ANFIS Models

Model	ANFIS Model (1)	ANFIS Model (2)	ANFIS Model (3)	ANFIS Model (4)
RMSE	52.45	45.58	57.58	70.52
MAE	30.09	25.73	28.73	28.09
MPE	1.22	1.15	1.50	1.29

    v)   Fitting for Observations Used in Training:

The fitting of the data using the two proposed techniques for observations previously used in training is presented in Table (7). It is clear that, The ANFIS Model is more closely to the measured values than the Combined Model (REGARIMA).
In Table (8) The RMSE, and MAE of the ANFIS Model is lower than the Combined Model. However, The MPE in Two techniques is the same. So, The ANFIS Model is more accurate than the Combined REGARIMA Model.

  E) Comparisons of The Two Approaches
     (Based on New Observations):

The comparison of the two forecasted electric load techniques are demonstrated in Table (9) with the actual "Measured" values.

Table (7) : Fitting Results for Observations Previously Used in Training

Obs	Measured	FORECAST		Abs. Percentage Error	
		ANFIS Model (2)	REG ARIMA (0,1,1)	ANFIS Model (2)	REG ARIMA (0,1,1)
183	2,546	2,494	2,520	0.02	0.01
222	2,492	2,379	2,371	0.05	0.05
366	2,175	2,174	2,168	0.00	0.00
549	2,502	2,535	2,589	0.01	0.03

It indicates that, the obtained forecasted values are close to the actual values. However, the forecasting results of the combined model (REGARIMA) are superior to the results of The ANFIS model. Furthermore, these observations are not used in training.

Table (8) : Comparison Between The Used Techniques

Model	RMSE	MAE	MPE
REGARIMA(0,1,1)	75.72	33.25	0.01
ANFIS Model (2)	64.35	16.75	0.01

Table (9) : Forecasting Results of The Two Approaches

Obs	Measured	FORECAST		Abs. Percentage Error	
		ANFIS Model (2)	REG ARIMA (0,1,1)	ANFIS Model (2)	REG ARIMA (0,1,1)
706	2,166.00	2,167.00	2,135.11	0.05	1.43
707	2,223.00	2,155.00	2,156.93	3.06	3.07
708	2,225.00	2,212.00	2,204.67	0.58	0.92
709	2,233.00	2,172.00	2,220.94	2.73	0.56
710	2,164.00	2,180.00	2,185.02	0.74	0.96
711	1,992.00	2,042.00	2,051.44	2.51	2.91
712	2,151.00	2,076.00	2,121.92	3.49	1.40
713	2,184.00	2,126.00	2,166.69	2.66	0.81
714	2,241.00	2,211.00	2,220.52	1.34	0.93
715	2,245.00	2,241.00	2,239.29	0.18	0.25
716	2,242.00	2,201.00	2,246.29	1.83	0.20

Table (10) shows The RMSE, MAE, and MPE. These indices are all the lowest for The REGARIMA model. The results obtained in the two approaches are very encouraging. Moreover, the maximum percentage error is less than 3.49% for both models which is very acceptable.

4. Conclusions:

The proposed hybrid model (REGARIMA) that combines the regression model, and ARIMA model technique proves to be slightly more efficient than the ANFIS Model for Short –Term Load Forecasting purposes. This stems from the fact that the ARIMA model is devoted solely to investigation of the random effects in the Peak Load Data. The proposed hybrid model was compared to different ANFIS models. Both techniques are promising for Short –Term Load Forecasting purposes. These ptposed techniques could be used in forecasting of wind speed as well.

Table (10): Comparison Between The Used Techniques

Model	RMSE	MAE	MPE
REGARIMA(0,1,1)	32.29	10.65	0. 46
ANFIS Model (2)	45.58	25.73	1.15

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