



# An Incremental Deep Model For Computing Electrical Power Load Forecasting Based Social Factors

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## ABSTRACT

Load forecasting (LF) is critical for guaranteeing adequate limit and controlling of the power business in numerous nations, which the economies depending on electricity. Its production (load) and consumption (demand) have to be in equilibrium at all times since storing electricity, in a considerable quantity, results in high costs. Therefore, the forecasting of the electrical load problem in many countries become crucial and critical in the recent years. In this paper, a novel deep model architecture for LF introduced, which integrates the features of dataset in discovering the most influent factors affecting electrical load usage. In addition, different LF strategies introduced and their interrelations just as the intensity of neural organizations to rough the heap estimating. The deep model is based on in three terms time: Long-term (yearly), Mid-term (Monthly), and Mid-term (Weekly), which can possibly provide interrelated deep learning models. Moreover, to generating more accurate predictions based the hierarchal learning architecture. The dataset used is introduced in the case study, which is power load in Giga-watt from years 2006 to 2015. The load forecasted for the year 2016 and is validated to check its accuracy.

**Key words:** Deep Model, Forecasting, Load, Electric, Factors, Artificial Intelligent, Learning, Economic.

## 1. INTRODUCTION

Electric load forecasting can be defined as a realistic estimate of future demand of power [1]. As such, load determining is a method of assessing what future electric burden will be for a given figure skyline dependent on the accessible data. [2]. All over the world, electrical power plays a key role in supporting national economy. This economic and social significance has increased the importance of electrical load prediction research [15]. Forecasting in power systems helps in many processes such as the operation of power systems; transport networks and logistics management [3]. Additionally, forecasting of future loads is also a basic step for network planning, infrastructure development since infrastructure and great estimates can save a large part of investments [4, 5, 6].

As known, it is hard to store critical amounts of power. Consequently, it is fundamental, constantly, to keep up balance between creation and utilization [7]. Therefore, accuracy is required for load forecasts, the economy of operation and the control of the power system, which may be quite sensitive to

forecasting errors [8]. A conservative estimate, by Hobbs et al. [9], showed that a reduction in the load forecasting error by 1 % lowered the costs by \$1.6 million annually [7]. In recent years, prediction efforts have shifted from annual to daily, hourly, and even order of few minutes' consumption prediction. The public load-forecasting classification are [10, 11]:

- 1 year: Long Term Load-Forecasting (LTLF)
- Under 1 year: Medium-Term Load Forecasting (MTLF)
- Under one week: Short-Term Load-Forecasting (STLF) and
- 1 hour : Very Short-Term Load-Forecasting (VSTLF)

Therefore, modeling and forecasting electrical energy consumption has been an active research area for more than three decades. Artificial neural networks (ANN) has broadly studied for electric load forecasting [18]. NN is essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting, filtering and prediction. In the same vein, a lot of methods and algorithms would be used and a lot of machines learning algorithms used in analysis and classify data of power system such as Support Vector Machine (SVM) [8,10].

Based on the above overview, there is needed to participate the features of learning determining the most factors that affect power load usage. This paper proposed a deep model, which incorporates the features of data set in determining the most factors affecting electrical load usage. In addition, the paper introduce the model that employ machine learning and regression techniques.

The rest of the paper, Section-2 explain the related work. Section-3 presents the proposed deep model for load forecasting. Section-4 presents the methodology; will Section-5 discussed the experiments and case study. We close with the concluding in section-6.

## 2. LITERATURE REVIEW

The works of load forecasting founded back to at least-1918 [30]. A time series, with the load series can disintegrated to organized variation and sound. The techniques and variables are the most of the model improvement work, which can classified in to statistical approaches, such as regression analysis and time series analysis, and artificial intelligence (AI) based approaches, such as NN, Fuzzy-Logic (FL), and Support-Vector-Machine (SVM) [10].

Load forecast models can be divided into two groups based on the relationship with external factors: time-of-day models and dynamic models. Time-of-day model only depends on discrete time series that consists of load values for each time step of the forecasting period. Whereas the dynamic model that is based on the fact that the load is not only a function of the time of the day, but also of the load most recent behavior [8].

Another classification of the load forecasting methods is based on their degrees of mathematical analysis used in the forecasting model, namely: quantitative and qualitative methods [8]. Qualitative forecasting methods are used when historical data are not sufficient or not available at all and sometimes, data can be anticipated. The statistical category includes multiple linear regression, stochastic time series [3], general exponential smoothing [28], state space, Support Vector Regression (SVR) [31]. The artificial intelligence methods include neural networks [40, 20, 22], support vector machines [26], genetic algorithms [14], wavelet networks [12, 13], fuzzy logics [16] and expert system [21] methods. In fields

such as economics, optical signal processing as well as electric load forecasting, time series have been used for decades. Models of time series include “ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average) and ARIMAX (autoregressive integrated moving average with exogenous variables). ARMA models are usually used for stationary processes, while ARIMA, an extension of ARMA, is used for non-stationary processes. Both ARMA and ARIMA use the time and load as the only input parameters, while ARIMAX adds exogenous variables to its formulation. As explained, load generally greatly affected by the weather along with time of the day; ARIMAX is the most reliable tool for LF among the classical time series models [25]. Moreover, Artificial intelligence based methods are SVM based methods, Evolutionary computing/ Genetic based methods, Wavelets based methods, Fuzzy logic systems and Rule based/Expert systems forecasting. Table 1 shows the comparison for load forecasting based approach based factors, the general criteria are presented.

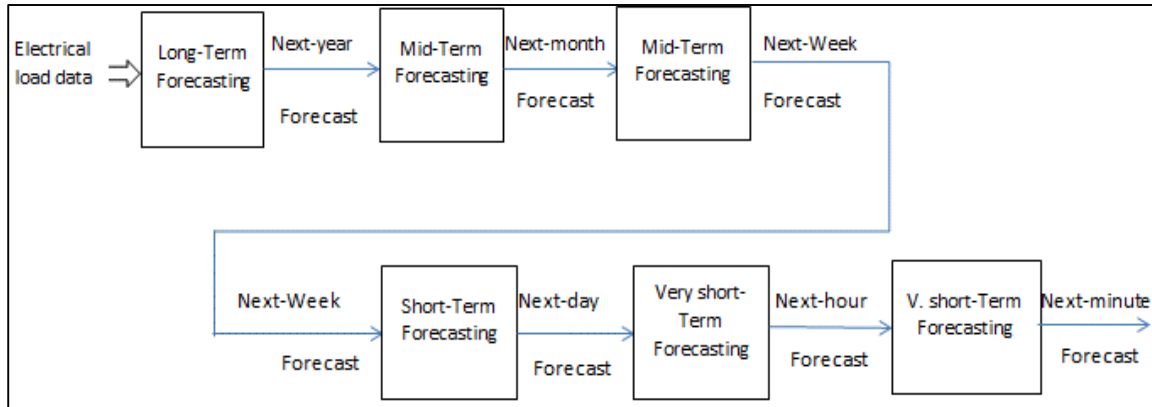
Table 1: Load forecasting approaches based factors

Author	Objectives	Factors included	Model	Application Area
KHAIR, et al 2017	Propose DAILY STREAMFLOW PREDICTION ON TIME SERIES FORECASTING	Historical load	SVM Regression, Multilayer Perception	Region in malaysia
Daniel, et al, 2016	Building Energy Load Forecasting using Deep Neural Networks	DEC 2006 and November 2010 with one-minute resolution	Long Short Term Memory (LSTM) algorithms, DNN	single residential customer, “Individual household
Stefan et al, 2016	Short term Load Forecasting using Deep Neural Networks	Load , and Even for weekdays.	DNN	aken from periodic smart meter energy usage reports
Ming-Yue Zhai 2015	Load forecasting based on fractal interpolation, short term	self-similarity theory and fractal interpolation. wavelet analysis	Parameter estimation fractalinterpolatio and extrapolation	Shanxi Province
Wan, 2014	proposed Deep neural network based load forecast.	various features	DNN	Region in china
Hong, Tao, 2014	Enhance and defensible forecasts, long term	scenario analysis, and weather normalization	Multiplelinear regression models,	North Carolina Electric
Ceperic, et al 2013	“Reduce the operator interaction in the model-building procedure“	temperature, humidity, air pressure, seasonal period, holiday season	Support Vector Regression Machines	Al Batinah - Oman
SWAROe t al.. 2012	“prediction the amount of electricity needed for better load distribution“	Temperature, Humidity	Neural Network	Malaysian electricity
Farahat, et al. 2010	“Design a compact, fast and accurate model to improve the short-term load forecasting“	“Temperature, relative humidity, wind speed and cloud cover. ARIMA”	Curve vetting, Genetic Algorithms	daily and hourly loads in North America
Shankar, et al. 2012	automatic generation control of multi generating power unit of the interconnected power system	relationship between the economic load dispatch and load forecasting mechanism	economic, Kalman filter	India
Shu Fan, et al 2010	Prediction, semi-parametric additive models	Calendar variables, lagged actual demand observations , historical, and forecast temperature traces.	Artificial Neural Network	Australia
Stojanovi´ c, et al. 2010	“Predict maximum daily load for period of one month, using different data sets and features”.	Maximum-daily load for past seven days, Average-daily temperatures (T)	SVM	“Eastern Slovakian Electricity

### 3. The MODEL ARCHITECTURE

The proposed model aims to improve load forecasting using social and economic factors. The time series forecasting for

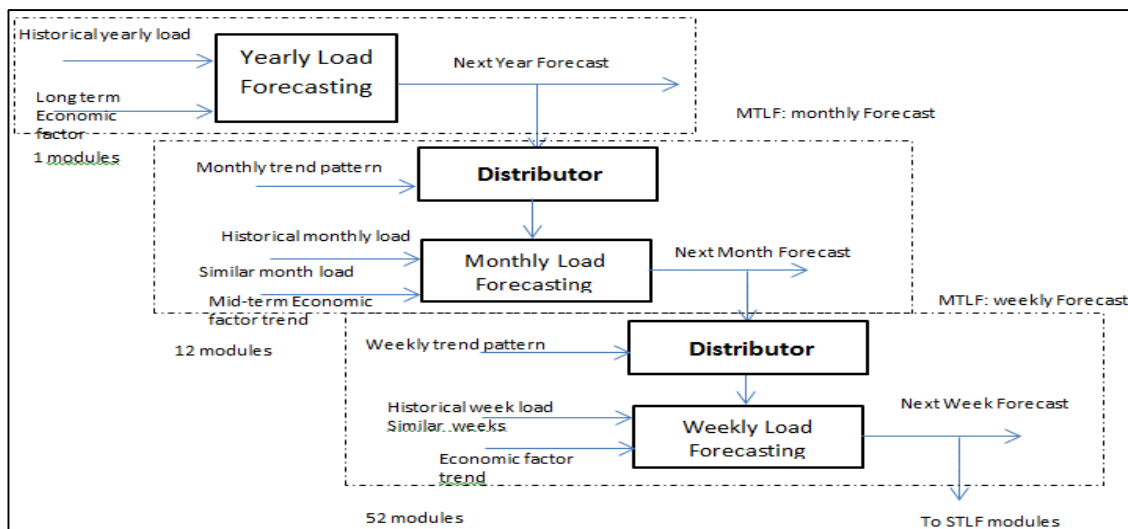
every factor is presented. Three modules are proposed and presented, which are long-term approach, mid-term approach, short-term, very short, and ultra-short approaches. Figure 1 show the cascaded layers for load forecasting.



**Figure 1:** Cascaded Layers for Load Forecasting model

Moreover, factors affecting the load at different time horizons {ultra-short, very short, short, medium, long} are different from one time horizon to another. The factors in the short-term load depend heavily on time factors (for example hour of the day, day of the week etc.). Medium to long term load is affected by factors such as population growth, per capital

income, demographic factors, Gross Domestic Product (GDP) and so on. Most power systems use this distinguishing dependence in choosing the input variables. Figure: 2 presents the modules for long-term and Mid-terms (monthly and weekly) modules for the load forecasting model. Each model is illustrated in details as follows.



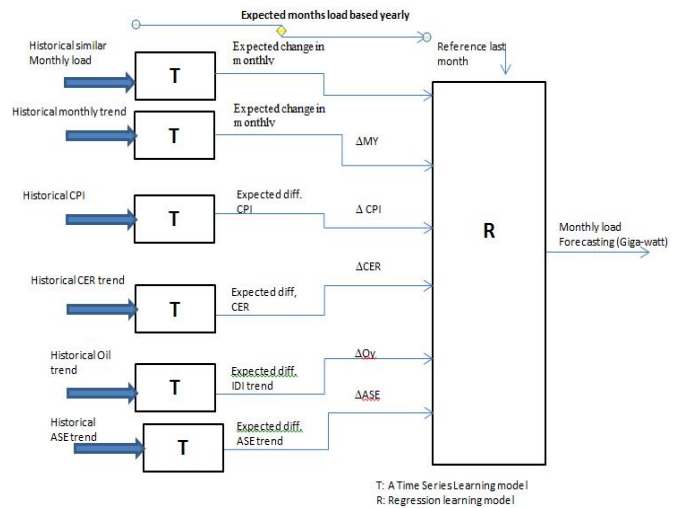
**Figure 2:** Long, Mid and Short Term modules based model for Load Forecasting

Table 2 demonstrates a list of measurable factors that should be considered in order to minimize the risk of load variations. The forecast time horizon determines which factors could be selected in the design of input vector of a forecasting model.

**Table 2:** A measurable factors of the different time horizons

Time Horizon	Long term	Med-term	Short term
Proposed time	Year	• Month & Week	Day
Factors	<ul style="list-style-type: none"> <li>• Population growth trend</li> <li>• Gross Domestic Product (GDP) trend</li> <li>• Currency Exchange Rate (CER) trend</li> <li>• Expected average oil price (in Arab gulf countries)</li> <li>• Electricity price</li> <li>• Long term trend</li> </ul>	<ul style="list-style-type: none"> <li>• Per <b>capital income</b></li> <li>• Consumer Price Index (CPI)</li> <li>• Average Salary Earning (ASE)</li> <li>• Seasonal pattern: {summer, winter,...}</li> <li>• Currency Exchange Rate (CER)</li> <li>• Industrial Index (IDI)</li> <li>• Stock Market Indicator (SMI)</li> <li>• Electricity price</li> <li>• Expected long term variation</li> </ul>	<ul style="list-style-type: none"> <li>• Day type</li> <li>• Weather data                             <ul style="list-style-type: none"> <li>• Temperature</li> <li>• Humidity</li> <li>• wind</li> </ul> </li> <li>• seasonality effect (special days)</li> <li>• short term trend (similar days trend)</li> <li>Expected med-term variation</li> </ul>

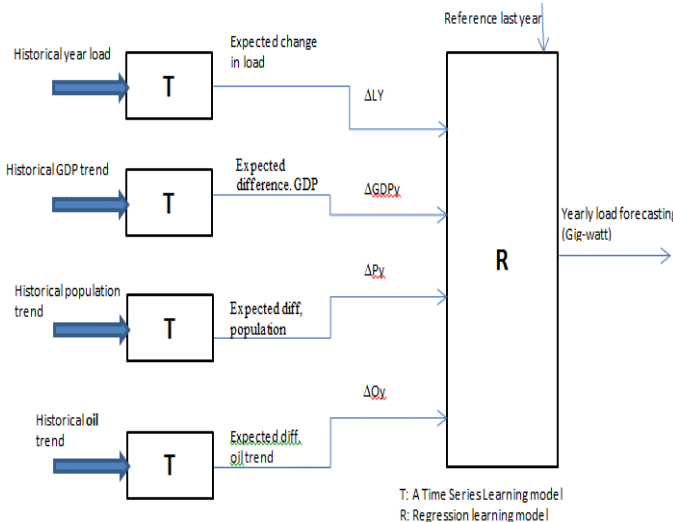
Price Index (CPI), Currency Earning Rate (CER), and Average Salary Earing (ASE).



**Figure 4:** Mid-term-monthly load forecasting

**a. Long-Term Yearly Load-Forecasting Model**

Figure 3 shows the long term model for the LF prediction architecture. The model contains of the greatest factors used based learning, which are historical load in Giga-watt hour, Gross Domestic (GD), Population, and Oil-price (OP), where (T) represents time series learning unit, and (R) represents a regression learning unit.



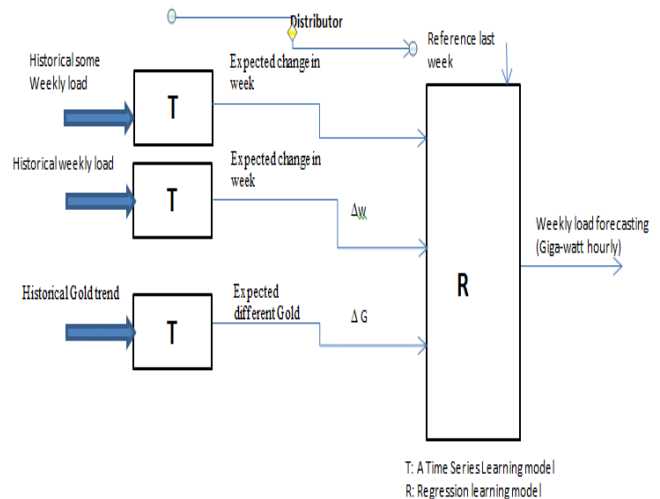
**Figure 3** Long term load forecasting

**b. Mid Term monthly Load Forecasting Model**

Figure 4 show the mid-term load forecasting model architecture, the factor used based learning are: Consumer

**c. Short Term weekly Load Forecasting Model**

Figure 5 show the mid-term load forecasting model architecture, the most important factors are studied, which are the historical load, and gold price/ (ounce USD).



**Figure 5:** Mid-term (weekly) load forecasting

The pseudo-code deep model for load forecasting presented in the figure 6.

```

Input: n = Historical data for load, f= Historical data for Factors.
Output: Load forecasting

Begin
  Initialize: LA0: Load, T: TS-RLS, R: Regression based-RLS, f: factors
               Lestt+1: Load estimate forecasted, LTLF=10
               Year, MTLF= 10*12 (12 module) months, 52
               (module) week.
  Get Data from forecasting Upper layer
  // works only for mid-term forecasting
  Function Distributed month (i) // distributor for monthly and
  weekly
  Current estimation // estimated for
  Months or Weeks
  // Time series Recursive least square (TS-RLS) Procedure
  For i: 1 to n Do
    Forecasting for Historical data
    For each factors
      Compute predict value for each factor based on TS-
      RLS
      Add vector for evaluate f(t-1), and
    Add vector Reference for last estimate last for (months or week)
  End for
  Function TSRLS module of learning // Updating Rule
  Wk = WR-1 - KR (XTR WR-1 - yTR)
  TSRLS.Update ()
  Return TSRLS ()
  // Recursive least square (RLS) procedure
  
```

Figure 6: pseudo-code for LF

#### 4. METHODOLOGY PROCESS

Figure 7 presents the approach process for LF model. The methodology architecture contains five stages, which are Historical-Load for Previous data, weather data, Forecaster, other factor forecast (economic, social, etc), Time-series forecasting, Training forecasting, prediction, and LF predict (GWh).

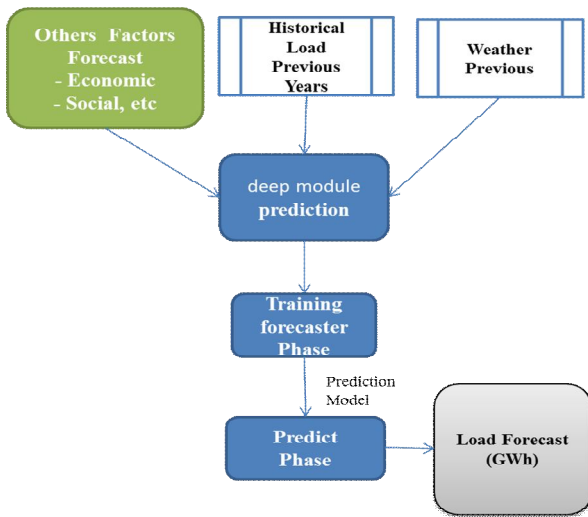


Figure 7: Methodology for proposed Load forecasting

Based on the methodology, the dataset based model under goes into two main processes: time-series forecasting and predict phase.

- a) Time series Recursive least square (TS-RLS): In this process, the factors in dataset go into time-series forecasting process.
- b) Recursive least square (RLS): In this step, we basically build a linear model for forecasting based on regression using current values. This process is based on the two general models: OLSR (Ordinary Least Squares Regression), and NN (Neural Network).

#### 5. CASE STUDY

The datasets used in the experiments is trained and tested; the experimental discussed for the Long-term (yearly) forecasting, Mid-term (monthly) forecasting, and Mid-term (weekly) forecasting. The results for proposed methods will be compared with an existing state-of-the-art method, and finally the computational efficiency of the method will be discussed. In the experimental results, the learning module forecasting and regression forecasting applied.

##### 5.1. Data Collection

The data set in this paper is the actual data from Ministry of Electrical in the Kuwait. The data set collected for the power load in Giga-watt-hour. In addition, several economics and social factors in the Kuwait region for 10 years from 2006 to 2015. Representative variables that are used as input to our deep load prediction model have been considered on the basis of these studies.

In this paper, we focus on the load periodicity, Oil price, Gross-Domestic, Population (GDP), Passengers, Residence, Currency-Earning Rate (CER), Average-Salary, and economic factors like (total import and export in USD). Table 3 shows list of all factors. The proposed model based approach executed using GRETL\_tool. The GRETL tool is a cross-platform software package for econometric analysis, Gnu Regression, Econometrics and Time-series Library such as Auto Regression (AR). It is free, open-source software.

**Table 3:** List of Data collection

Year	Max_Load	Temp.	Humidity	Oil_Price_ \$	Total_jmp\$	Total_Exp. Oil_ \$	Total_Exp. p Others\$	Gross Domestic Billion_ \$	Population	Passengers-Arrivals	Residence	CER	ASE
2006	8962.23	49.6	98.3	74.2236	16501673	5.09062e+007	2716610	101.55	2389498	6100000	1633327	0.290	1050
2007	9080.80	49.6	98.3	75.0232	20002848	5.53626e+007	3267548	114.64	2538591	7137000	1715458	0.280	1100
2008	9710.19	50.0	100.0	76.8542	22039703	7.31884e+007	4228765	147.40	2705290	7493850	1806210	0.270	1100
2009	9974.47	48.8	100.0	69.0437	18884283	4.44792e+007	4804576	105.90	2881243	8168296	1934272	0.290	1250
2010	10916.00	51.1	90.2	82.4223	21445403	5.49424e+007	4323116	115.42	3059473	8513345	2084144	0.290	1250
2011	11236.50	51.1	91.0	110.0117	22895615	8.8667e+007	4854544	154.03	3239181	8426737	2166275	0.280	1376
2012	11894.80	51.2	93.0	106.5786	25184607	1.00243e+008	5526649	174.07	3419581	8877883	2257027	0.280	1420
2013	12066.60	50.4	100.0	103.7324	27419192	1.00668e+008	6131228	174.16	3593689	8000000	2385089	0.285	1420
2014	12422.00	56.1	96.0	80.1537	29136749	8.8551e+007	5949385	153.61	3753121	10027000	2468018	0.285	1500
2015	12797.50	50.8	100.0	42.3984	30743137	4.81188e+007	5605872	112.81	3892115	10400000	2592276	0.303	1650

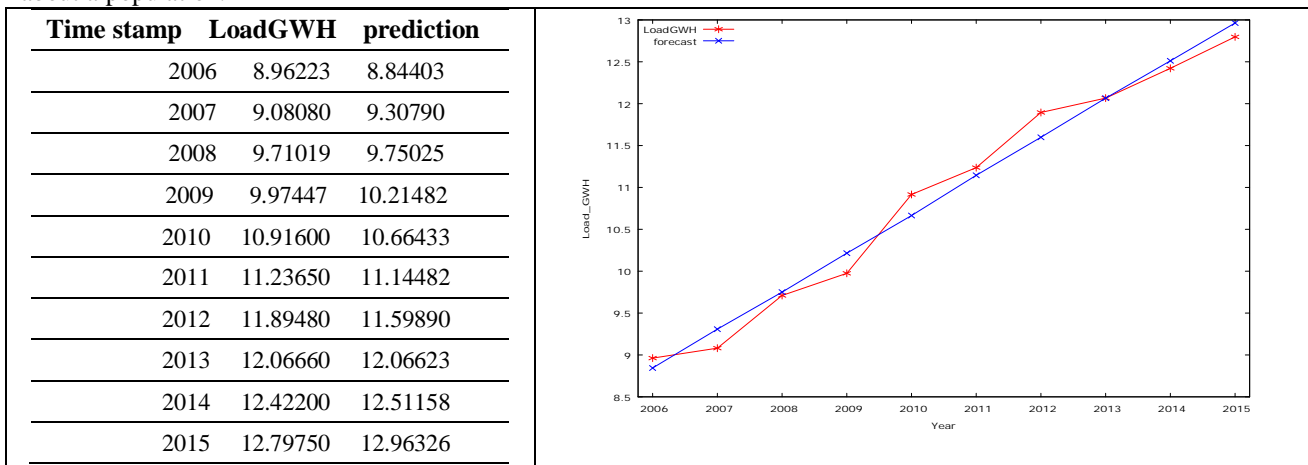
**5.2 The Load forecasting Experimental Results**

The experiments are implemented for the best forecasting model after a set of trying experiments. The best model given the forecast results near the actual data. In the following the details for each experiments terms is described.

A *p*-value helps you determine the significance of the results. In order to test the validity of a claim that is made about a population.

**- Experiment for Long-term load forecasting(LTLF)**

The experiment in figure 8 shows the forecasting for each factor in the long-term, and the second is the regression forecasting for all factors based on Load\_GWH as a dependent variable layer.



**Figure 8:** The result for Load\_GWH forecasting long-term

**- Long-term Load forecasting based factors regression**

The proposed Long-Term is trained using the actual data for long-term 10-years from (2006-2015). The Model Ordinary Least Squares Regression(OLSR) is used for observations 2006-2015 (T = 10), and dependent variable is Load\_GWH as shown in table 4.

**Table 4:** The load\_MWH using OLS model

	std.error	p-value
Oil_Price/drum	0.005248	<b>0.2588</b>
Gross_domestic10~	0.004377	<b>0.627</b>
Population	1.57E-07	<b>2.30E-06</b>

**- Long-term load forecasting for year (2016)**

In this experiment, it is assumed that the data for 2016 is not included. The forecasting is based on historical data from (2006-2015). The OLS model is used for the observations 2006-2015 (T = 10), with dependent variable: LoadGWH. Table 5 shows load\_MWH using OLS model, while Table 6 shows result of load forecast for future year 2016. Figure 9 shows the curve for actual and forecast for year 2016:

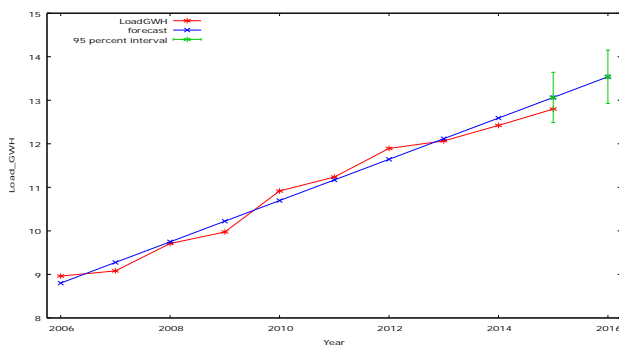
**Table 5:** The load\_MWH using OLS model

	std.error	p-value
Oil_Price/drum	0.008425	0.4173
Gross_domestic10~	0.00509	0.7790
Population	8.00364e-06	0.4968

Table 6: result of load forecast for future year 2016

2015	12.7975	13.0649	0.24437	-12.4871	13.6427
		3			7
<b>2016</b>		<b>13.5387</b>	0.25862	-2.9272	14.1502

Root Mean Squared Error 0.26110  
 Mean Absolute Percentage Error (MAPE) **0.9464**

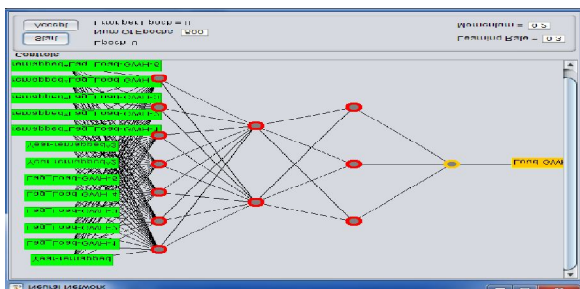


**Figure 9:** The results for LF for actual years (2006-2015) and forecast load\_Gwh curve for year 2016

**-Long-term load forecast for suggested year (2016) using neural network**

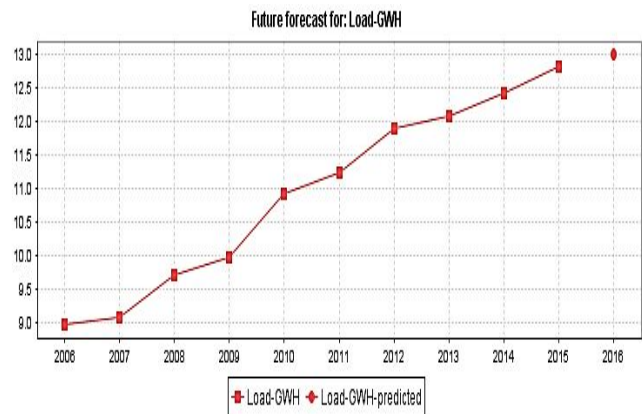
In this experiment, the NN is implemented, which the number of Hidden Layers (HL) used are HL=2, HL=3, and HL=4. The experiments were conducted using Weka Environment for Knowledge Acquisition (WEKA), where NN is already implemented in Java. Figure 11 shows the network for HL=2, and Figure 8 shows the network for HL=3, HL=4.

Attributes of the experiment are: Hidden Layers (HL) = 2, Scheme: Multilayer Perceptron -L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H "a, 2, 3" -G -R, Relation: LOAD\_YEAR, Instances: 10, Attributes: 5, Year, Load-GWH, Oil\_Price per drum, Gross\_domestic(1000Million), Population



**Figure 10:** A neural network for long-term model of HL=2

Time	Load-GWH
2006	8.962
2007	9.081
2008	9.71
2009	9.974
2010	10.916
2011	11.237
2012	11.895
2013	12.067
2014	12.422
2015	12.798
<b>2016*</b>	<b>12.9828</b>



**Figure 11:** the predicted results long-term forecasting using NN, HL=2

**6. CONCLUSIONS**

In this paper, we proposed an efficient deep model for load forecasting based on in three time horizons: Long-term (yearly), Mid-term (Monthly), and Mid-term (Weekly), which can possibly provide deep learning models to load forecasting. The model is incorporating the features of data in discovering the most influent factors affecting in load forecasting. In addition, it presents a deep learning model for load forecasting that takes into consideration the actual factors that affects the electrical usage. This model was compared with other methods. The results were better in which the Avg. MAPE 0.9464, compared to NN 15.4 where HL=2 and 4. The performance measures such as error rate was better for NN, which proves the idea of decomposition. Distributed deep learning model can provide an efficient and reliable model for LF. In order to build a reliable LF system, the reliability and robustness of the system principally rely on the accuracy of the forecasts.

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