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LONG-TERM DEEP LEARNING LOAD FORECASTING BASED ON SOCIAL AND ECONOMIC FACTORS IN THE KUWAIT REGION

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ABSTRACT

Load forecasting (LF) is a technique used by energy-providing companies to predict the power needed. LF is of great importance for ensuring sufficient capacity and manipulating the deregulation of the power industry in many countries, such as Arab gulf countries. Moreover, reduction of load forecasting error leads to lower costs and could save billions of dollars. Recently, further improvement has been introduced using more complex models that take into account dependencies among hidden layers. Also, many approach based model are presented, but all of them have limitations prediction capabilities. The purpose of this work is to demonstrate the load forecasting classes and factors impacting its performance, especially in Kuwaiti region in Arab Gulf. This work presents a novel deep leaning model that involves generating more accurate predictions for the electric load based on hierarchal learning architecture. It is integrates the features of data in discovering most influent factors affecting electrical load usage. The dataset used is the actual data from Ministry of Electrical in Kuwait, the data for load is in mega-watt long-term for the years 2006 to year 2015, which is trained using ARIMA and neural networks models. The load forecasting is done for the year 2016 and is validated for the accuracy and less for error rate. Results indicate that this architecture performs quite well when compared to traditional approaches and deep neural network.

Keywords: *Power Electricity; Load forecasting; ARIMA; Regression; Long-term; Prediction; deep learning;*

1. INTRODUCTION

Forecasting is the process of estimating the qualitative or quantitative future data by means of calculation. Forecasting has been applied in many areas and it is sometimes human driven due to its complexity. It could be considered one of the most difficult tasks because of the uncertainty about the future [1]. Load forecasting is a technique used by energy-providing companies to predict the power/energy needed to meet the demand and supply equilibrium. Its importance in business, economics, government, and many other fields, and guide many important decisions [2]. Therefore, good forecasts help to produce good decisions such as decisions on purchasing and generating electric power, load switching, and infrastructure development [3].

Basically, an electric load refers to the power consumed by an electric circuit at its output terminal [5]. In other words, load forecasting is way of estimating what future electric load will be for a given forecast horizon based on the available information about the state of the system [6]. In addition, forecasting is inextricably linked to building statistical models before forecast a variable of interest, also, build a model and estimate the model's parameters using observed historical data. Typically, estimated model summarizes dynamic patterns in the data [6], which is estimates model provides a statistical characterization of the links between the present and the past data.

Therefore, the important factors for load forecasting are dynamic patterns data, statistical characterization of the links between the present and the past data. Such as, Time factors: the similar day approach, the Weather factor such as temperature and humidity, etc. in addition, the Time factors include the time of the year, the day of the week, and the hour of the day. There are

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important differences in load between weekdays and weekend [6] [8]. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday.

On the other hand, Deep Learning (DL) is a new area of Machine Learning research, which has been introduced with the objective of moving Machine Learning closer to one of its original goals: Artificial Intelligence. DL allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction.

In other hand, forecasts can also be classified based on the forecasting horizon. A common classification of load forecasting used in [17], as the following [18]:

- Very Short-Term Load Forecasting (VSTLF): A forecasting horizon of under 1 hour;
- Short-Term Load Forecasting (STLF): A forecasting horizon of under one week;
- Medium-Term Load Forecasting (MTLF): A forecasting horizon of under 1 year; and
- Long-Term Load Forecasting (LTLF): A forecasting horizon of over 1 year. Table 1 shows taxonomy of load forecasting.

Table 1: Taxonomy of Load Forecasting [16]

Load Forecast	Period	Importance
Long	1-10 Years	To calculate and to allocate the required future capacity. To plan for new power station to face customer requirements Plays an essential role to determine future budget.
Medium	1-week to few months	Fuel allocation and maintenance schedules Accurate for power system operation.
Short	1-hour to 1-week	To evaluate economic dispatch, hydro-thermal co-ordination, unit commitment, transaction. To analysis system security among other mandatory function.
Very-Short	1-minite -1-hour	Energy management system(EMS)

Time series prediction can be divided into two categories depending on prediction time period: short term and long term [18]. The forecasting algorithms aim to forecast future values based on the present and historical data. The tools for prediction include: neural networks, regression, Support Vector Machine (SVM), and discriminate analysis. Recently, data mining techniques such as neural networks, fuzzy logic systems, genetic algorithms and rough set theory are used to predict control and failure detection tasks [5]. Most forecast use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. For example, Chen et al. [4] presented an additive model that takes the form of predicting load as the function of four components:

$$L = Ln + LW + Ls + Lr$$

where L is the total load, Ln represents the "normal" part of the load, which is a set of standardized load shapes for each "type" of day that has been identified as occurring throughout the year, Lw represents the weather sensitive part of the load, Ls is a special event component that create a substantial deviation from the usual load pattern, and Lr is a completely random term the noise.

1.1. The forecasting method and techniques

Based on the relation with external factors, load forecasting models can be classified into two categories: time-of-day models and dynamic models. Parametric load forecasting methods can be implemented using regression methods, time series prediction methods. For decades, time series have been used in fields such as economics, digital signal processing as well as electric load forecasting. Models of time series include ARIMA (autoregressive integrated moving average) and ARIMAX (autoregressive integrated moving average with exogenous variables).

a) **Statistical model-based learning:** The end-use and econometric methods require a large amount of information relevant to appliances, customers, economics, etc. In order to simplify the medium-term forecasts, make them more accurate, and avoid the use of the unavailable information, the following multiplicative model is the most accurate as shows in equation1.

$$L(t) = F(d(t), h(t)) - f(w(t)) + R(t) \quad (1)$$

where L(t) is the actual load at time t, d(t) is the day of the week, h(t) is the hour of the day, F(d, h) is the daily and hourly component, w(t) is the weather data that include the temperature and humidity, f(w) is the weather factor, and R(t) is a random error.

In fact, w (t) is a vector that consists of the current and lagged weather variables. To estimate the weather factor f (w) based on the regression model as in equation 2.

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$$f(w) = {}^{\beta}o + \sum {}^{\beta}j\ Xj$$
(2)

where Xj are explanatory variables which are nonlinear functions of current and past weather parameters and β0, βj are the regression coefficients.

b) Time Series: Time Series Analysis Regression techniques were combined with ARIMA models. Regression techniques were used to model and forecast the peak and trough load. Then ARIMA was applied to a weather normalized load to produce the forecast. Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation.

c) Regression methods: Regression is the one of most widely used statistical techniques. For electric load forecasting regression, methods are usually used to model the relationship of load consumption and other factors such as weather, day type, and customer class.

d) Neural Networks (NN)**:** The have been a widely studied electric load forecasting technique since 1990. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or nonlinear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. The most popular artificial neural network architecture for electric load forecasting is **back propagation**. Back propagation neural networks use continuously valued functions and supervised learning. The under supervised learning, actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational "training session".

e) Support Vector Machine (SVM) is a more recent powerful technique for solving classification and regression problems. This approach was originated from statistical learning theory. Unlike neural networks, which try to define complex functions of the input feature space, support vector machines perform a nonlinear mapping (by using so-called kernel functions) of the data into a high dimensional (feature) space. Support vector machines use simple linear functions to create linear decision boundaries in the new space. Mohandes [3] applied support vector machines for short-term electrical load forecasting. Chen et al. [2] proposed a SVM model to predict daily load demand of a month.

Many researchers in the load forecasting models in the electric power system based approach presented such as in machine learning techniques (SVM, NN, etc.) but all of them have limitations prediction capabilities. Therefore, the problem of forecasting the electrical load in Kuwait and Arab Gulf has become crucial and critical in the recent years. The increasing and fluctuating load consumption has led to several problems such as occasional network power fault and failure.

In this paper, a soft computing based deep learning model is introduced, its integrate the features of data in discovering the most influent factors affecting electrical load usage, and their interrelations as well as the power of linear regression and neural networks to approximate the load forecasting in order to introduce a model for load forecasting that takes into consideration the actual factors that affects the electrical usage. While the long term used in this approach. The dataset used in this paper is for the Kuwait Electricity Authority of DC Network for the last 10 years as long term taxonomy.

The rest of this paper is organized as follow: Section 2 presents the Related Work briefly. Section 3 describes the proposed model Architecture and methodology. Section 4 shows the experimental results and discussions. The paper is concluded in section 5.

2. RELATED WORK

Forecasting is a planning tool that helps management in its attempts to cope with the uncertainty of the future, relying mainly on data from the past and present, also analysis of trends [2]. Therefore, extracting the relevant information from the huge amount of data is highly complex, costly, and time consuming. This complex problem requires to using soft computing techniques to cope with large number of factors for the actual power generation needed. This section present briefly the researches for prediction load forecasting from three aspects: the techniques developed, the representative work done, and viruses parameter deployed.

A novel applied approach to data analysis for power system based on data mining theory presented in research [2], the authors develop new application to analysis data for electrical engineering, they conclude that the data mining adds useful techniques to many other fields such as

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information processing, pattern recognition and artificial intelligence etc.

In the load forecasting power system, the time-series factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently [6] [8].

Numerous methods and clustering algorithms have been planned previous to support clustering of time series data streams [4]. The paper [7], present a pragmatic methodology that can be used as a guide to construct Electric Power Load Forecasting models. This methodology is mainly based on decomposition and segmentation of the load time series. In his work, Azadeh et al as [25] have proposed an integrated fuzzy system, data mining and time series framework to estimate and predict electricity demand for seasonal and monthly changes in electricity consumption especially in developing countries such as China and Iran with non-stationary data. In [20] proposed an algorithm using an unsupervised/supervised learning concept and historical relationship between the load and temperature for a given season, day type and hour of the day. They used this algorithm to forecast hourly electric load with a lead time of 24 hrs.

In recent years, many deep learning methods have been shown to achieve state-of-the-art performance in many research areas: speech recognition [10], computer vision [23] and natural language processing [15]. This promise has not been demonstrated in other areas of computer science due to a lack of thorough research.

In addition, forecasting is predicting unknown or future values of other variables. It's achieved by subjecting a huge amount of data to a training rule known as supervised learning, by estimated values are compared with known results [19]. In the same aspect, a new type of data mining based on data analysis load forecasting and the fast diagnostic reasoning algorithm presented in the research [3], it has obvious advantages in dealing with a large number of power system data, the data were analyzed by a logical of the relevance degree. The authors combine data mining algorithms and the system improves state analysis and mining. They are conclude that the approach provide a great deal of information for aid decision making for planning and designing new electric power for enterprises.

Research [4] presents an overview of data mining techniques used in power systems. In his paper Azadeh et al. [25] proposed an integrated fuzzy system for data mining and time series framework to estimate and predict electricity demand for seasonal and monthly changes in electricity consumption especially in developing countries such as China and Iran with non-stationary data.

Table 2 shows the load forecasting approaches based Factors which are used.

Based on the previous works, many researchers worked in prediction load forecasting, and a lot of models for the electric power system based approach where presented such as in machine learning techniques (SVM, NN, etc.), but all of them have limitations prediction capabilities.

Therefore, the problem of forecasting the electrical load in Kuwait and Arab Gulf has become crucial and critical in the recent years. The increasing and fluctuating load consumption has led to several problems such as occasional network power fault and failure.

Table 2: Load Forecasting Approaches based Factors

#	Author	Objectives	Factors used	Model	Application Area
1	SWAROOP R, et al. 2012	prediction the amount of electricity needed for better load distribution	Temperature, Humidity	Neural Network	Al Batinah - Oman
2	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	Zagazig -Sharkia Network, Egyptian Electricity
3	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	the daily and hourly loads in North America
4	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

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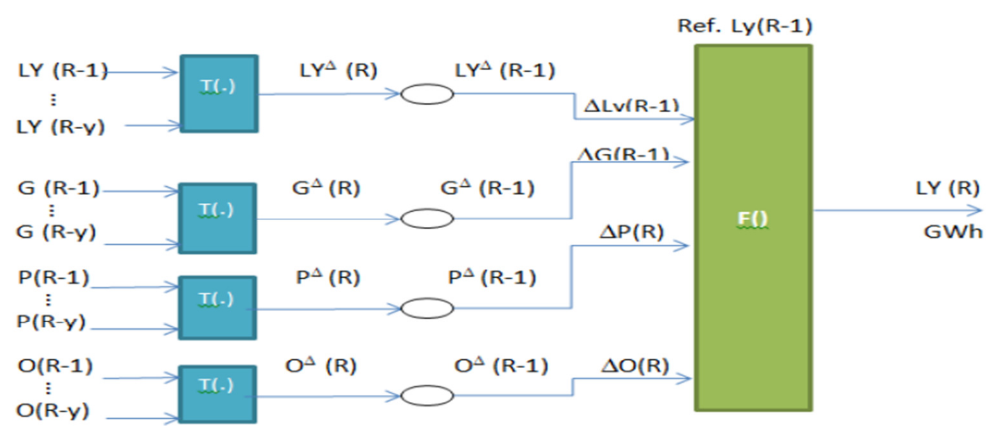
5	Stojanovi´c, et al.2010	Predict maximum daily load for period of one month, using different data sets and features	Maximum daily load for past seven days • Average daily temperatures (T), • Day Of the Week (D).	SVM	Eastern Slovakian Electricity Corporation for the EUNITE competition
6	Hinojosa, et al. 2011	apply fuzzy inductive reasoning (FIR) for Short-Term Load Forecasting in power systems	Weather and load) and qualitative variables (day, season, etc.)	ANN, fuzzy inductive reasoning (FIR)	Ecuadorian Energy Market
7	Guan, et al 2013	Very short-term load forecasting	Filter Wavelet Transform	neural networks	ISO New England.
8	Woo-Joo Lee et al. 2015	forecasting the electric power load, mid term	air temperature dependency of power load	fuzzy time series	Seoul metropolitan area
9	Hong, Tao, 2014	Enhance and defensible forecasts, long term	Predictive modeling, scenario analysis, and weather normalization	multiple linear regression models,	North Carolina Electric Membership Corporation
10	Riswan et al. 2015	daily forecasting of Malaysian electricity	Linguistic out-sample forecast by using the index numbers of linguistics approach.	fuzzy logical relationships	Malaysian electricity
11	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
12	Ming-Yue Zhai2015	Load forecasting based on fractal interpolation, short term	Self-similarity theory and fractal interpolation. wavelet analysis	Parameter estimation fractal interpolation and fractal extrapolation	Shanxi Province
13	X. Song 2006	new hybrid short-term load forecasting algorithm	temperature during spring, fall, and winter seasons is small	fuzzy linear regression method and general exponential smoothing	South Korea

3. THE PROPOSED SOFT COMPUTING MODEL BASED LONG-TERM FOR LOAD FORECASTING

Figure 1 show proposed long-term model for the load forecasting prediction architecture. The model consists of the most factors used based learning, which are: previous load in megawatt, Gross Domestic, Population, and Oil-price.



Ly: Electricity Load (GWh) in a Year, **G**: Gross domestic predict, **P**: Population, **O**: Oil price, **Ref**. energy: Reference.
T (.): a Time series function, **Ly** (y): Energy needed at Year (R), the current year, **F (.)**: forecast Regression function.

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Figure 1: The proposed long term model Architecture

a. Dataset

The dataset used in this paper is the actual data from Ministry of Electrical in the Kuwait. The dataset is for 10 years from (2006 to 2015), its yearly details for a set of electricity and social factors in the Golf Area (Kuwait), which are listed in the following: Factors for Load Forecast: **t**he real electrical loads are partial by a variety of factors. In this section, we study some of the most important factors. On the basis of these analyses, we consider extracting representative features which are used as input of our deep model for load prediction. We focus in this paper on load periodicity, time dependency, weather influence (temperature and humidity), Oil_price, Gross Domestic, Population, Passengers, Residence, Currency Earning Rate, Average Salary, and economic factors like (total import and export in USD). In the following, table 3 shows the list of all factors that are collected and under goes to forecast and predict with a sample data. While the figure 3 shows the time series trend for the sample factors.

Table 3: List of Data for the load forecasting, Economic and Social Factors

Year	Max_Load_ MW	Temp.	Humidity	Oil_Price_$	Total_imp$	Total_Exp. Oil-$	Total_Exp 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

Figure 4 shows the methodology for proposed long term load forecasting model. The model architecture consists of five modules which are: Historical Load for Previous Years, weather previous,
Model Forecaster, Load forecast, other factor forecast Time series forecasting, and Load forecasting predict (MW).

The data under goes into two main processes: time-series forecasting and prediction step.

1) Time-series forecast (TSF): every factor in dataset goes into time-series forecasting analysis, the algorithm used is ARIMA as shows in the following:

Given a time series of data Xt where t is an integer index and the Xt are real numbers, an ARMA (p, q) model is given by equivalently (3).

$$X_t - \alpha_1 X_{t-1} - \cdots - \alpha_{p'} X_{t-p'} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q},$$

(3)

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right) (1 - L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t$$

where L is the lag operator, the ά are the parameters of the autoregressive part of the model, the θ are the parameters of the moving average part and the ε are error terms. The error terms are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean.

2) Moving modeling in prediction: in this step, we basically build a linear model for forecasting using current values. Based in two general models: OLSR (Ordinary Least Squares Regression), and NN (Neural Network).

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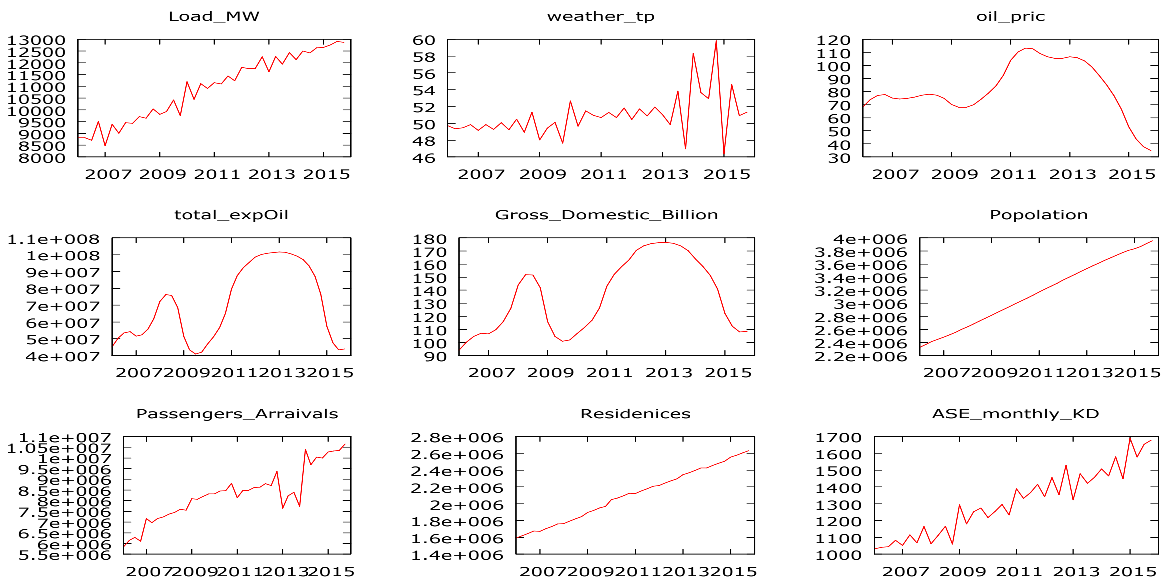

Figure 3: Time series trend for the factors used

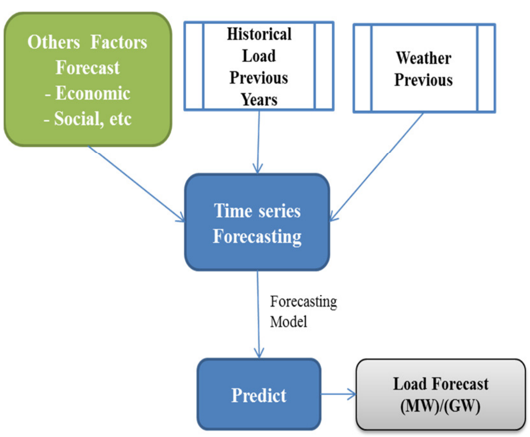

Figure 4: Methodology for proposed long term forecasting model

4. EXPERIMENTAL RESULTS AND DISCURSIONS

The proposed long-term load forecasting based approach has designed and implemented using the gretl[1]_tool. In the experimental results the time series forecasting and regression forecasting is applied. The gretl_tool is used. Gretl is a cross-platform software package for econometric analysis, Gnu Regression, Econometrics and Time-series Library. It is free, open-source software. There is a lot of forecasting model based regression in gretl_tool, which is used in the experiments. The best one for regression model used as in the follow:

a) Training the model forecasting using the actual data for long-term 10-years from (2006-2015). Model: OLSR, using observations 2006-2015 (T = 10), Dependent variable: Load_MW.

Table 4: OLSR model forecasting

Factors	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*
weather_temp.	38.1776	**79.1167**	0.4825	**0.6624**
Oil_price	4.94241	**7.32786**	0.6745	**0.5483**
Gross_Domestic_Billion	8.83792	**18.7439**	0.4715	**0.6694**
Population	−0.00144	**0.00838**	−0.1728	**0.8738**
CER_1KD_1USD	30026.9	**45957.3**	0.6534	**0.5601**
ASE_monthly_KD	−0.04242	**2.61026**	−0.0163	**0.9881**
Time	619.737	1226.6	0.5052	0.6482

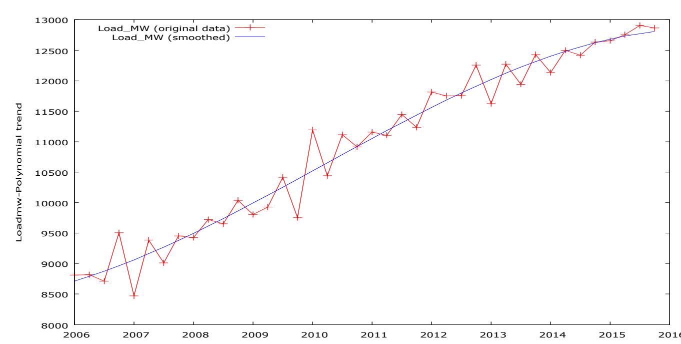

Figure 4: Load Megawatt Polynomial Trends

[1] http://gretl.sourceforge.net/

Table 4: Results for training model forecasting

Observation	Load_MW	**Prediction**	**std. error**	95% interval
2006	8962.23	8979.81	311.796	(7987.54, 9972.09)
2007	9080.80	9200.84	259.791	(8374.07, 10027.6)
2008	9710.19	9592.70	301.962	(8631.72, 10553.7)
2009	9974.47	10100.6	268.312	(9246.67, 10954.4)
2010	10916.0	10703.4	290.991	(9777.35, 11629.5)
2011	11236.5	11233.0	291.831	(10304.3, 12161.7)
2012	11894.8	11754.1	279.129	(10865.8, 12642.4)
2013	12066.6	12226.6	302.148	(11265.0, 13188.2)
2014	12422.0	12534.2	309.099	(11550.5, 13517.8)
2015	12797.5	12734.5	310.697	(11745.7, 13723.3)

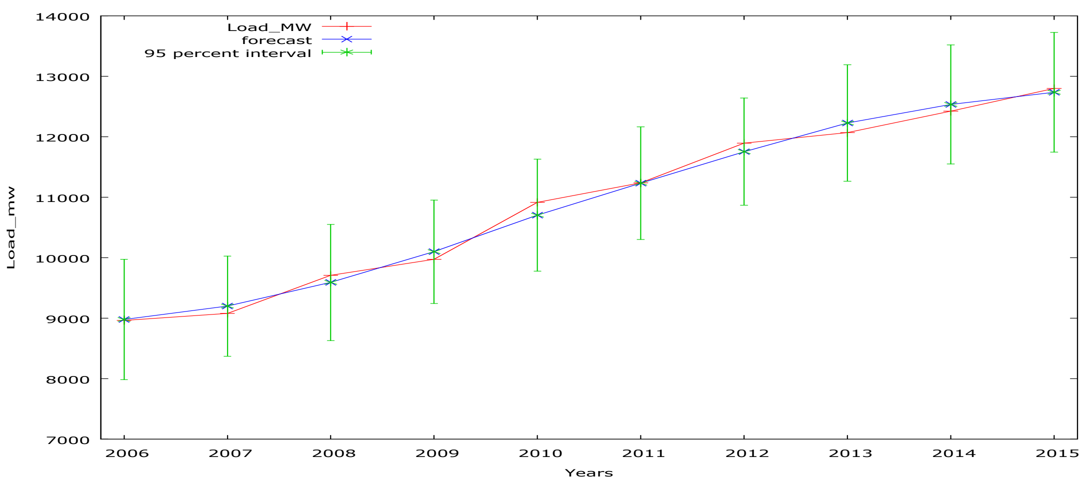

Figure 5: load Forecasting for years (2006-2015)

b) Load forecasting for the new year: after the training the model and approved the valid forecasting with near to the actual data, the load forecasting is done for new year as show in Table 5, which applied by using the regression model as shown in the follow: Regression without Time Series Model: Forecasting new year using OLS Regression for year from (2006-2015).

Table 5: Testing model forecasting for 95% confidence intervals, t (4, 0.025) = 2.776

Obs.	**Load_MW**	**prediction**	**std. error**	**95%interval**
2006	8962.23	8988.23		
2007	9080.8	9432.55		
2008	9710.19	9492.72		
2009	9974.47	10011.47		
2010	10916	10527.59		
2011	11236.5	11508.65		
2012	11894.8	11626.78		
2013	12066.6	12249.68		
2014	12422	12438.61		
2015	12797.5	12985.23	577.44	11382-14588.5
2016		**13637.4**	**1027.84**	10283.9-16990.9

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Forecast evaluation statistics:

Mean Error	-187.73
Mean Squared Error	35244
Root Mean Squared Error	187.73
Mean Absolute Error	187.73

Table 6: comparison for load_MW based factor (Population)

OLS, using observations 2006-2015 (T = 10)
Dependent variable: Load_MW

	Coefficient	***Std. Error***	*t-ratio*	***p-value***
const	2455.1	**362.681**	6.7693	**0.0001**
Population	0.00268527	0.000113856	23.5847	**<0.0001**

VAR system, lag order 1 Equation 1: Load_MW

	Coefficient	***Std. Error***	*t-ratio*	***p-value***
const	2776.82	**888.203**	3.1263	**0.0204**
Popolation	0.00344778	0.00116105	2.9695	**0.0250**

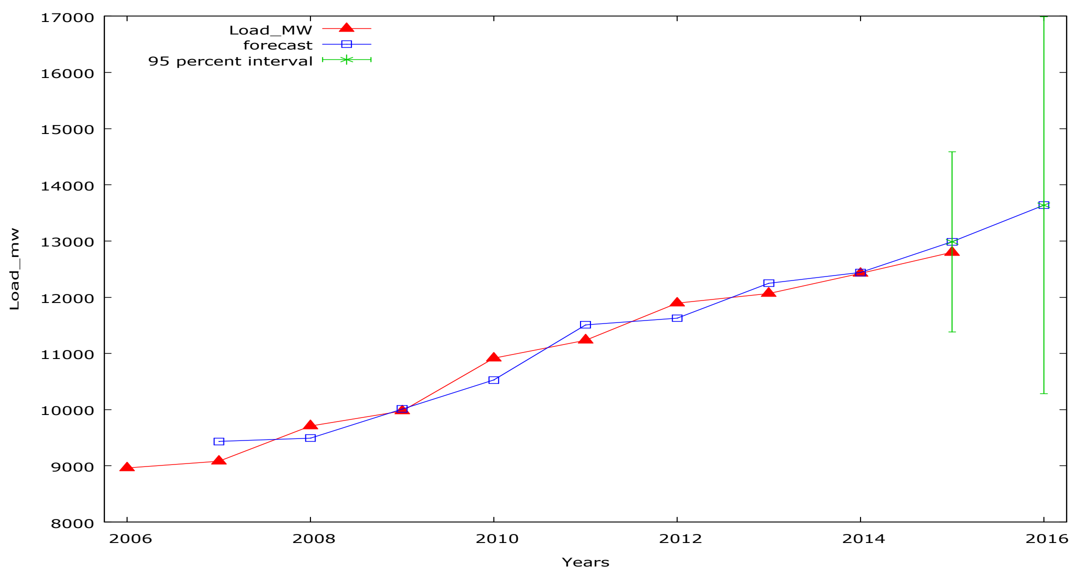

Figure 6: Load forecast for actual years (2006-2015) and forecast load curve for year 2016

c) Forecasting using neural network (nn) model

In this experiment the nn implemented, the number of hidden layers used are HL=2 with 5 nodes, and HL=3 with 10 nodes. The experiments were conducted using Weakaito Environment for Knowledge Acquisition (WEKA)[2]. where NN is already implemented in Java. Figure 7 shows the network for HL=2, and Figure 8 shows the network for HL=3.

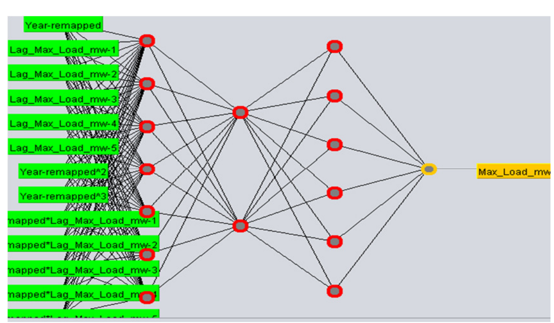

Figure 7: long-term forecasting using NN, HL=2

[2] http://www.cs.waikato.ac.nz

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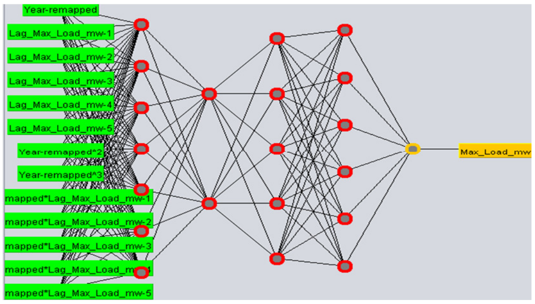

Figure 8: long-term forecasting using NN, HL=3

The time series using NN algorithm show in equation (4) and weight calculate in equation (5):

$$y_t = \Phi(\beta_0 + \sum_{i=1}^{q} \beta_i h_{it}), \quad (4)$$

where

$$h_{it} = \Psi(\gamma_{i0} + \sum \gamma_{ij} x_{jt}), i = 1, \ldots, q$$

where x_{jt} input and h hidden layer with q neurons, yt is output.

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial I_B} O_A \quad (5)$$

The weight change of W_{AB} depends on sensitivity of the square error, E^2 to the input, I_B of unit B and on the input.

Table 7: long- term results predicted using NN model

Obs.	Max_Load_mw 2 Hidden Layers	Max_Load_mw 3 Hidden Layers
2006	8962.23	8962.23
2007	9080.8	9080.8
2008	9710.19	9710.19
2009	9974.47	9974.47
2010	10916	10916
2011	11236.5	11236.5
2012	11894.8	11894.8
2013	12066.6	12066.6
2014	12422	12422
2015	12797.5	12797.5
2016*	**12906.584**	**12592.3666**

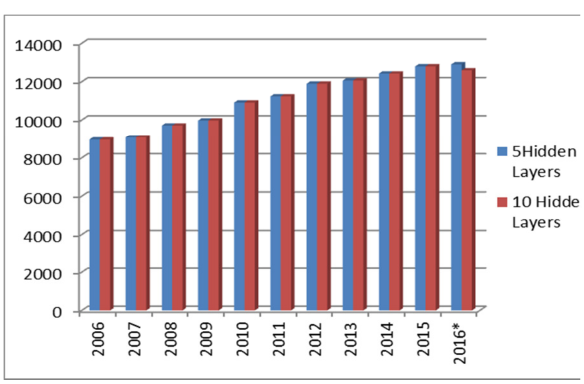

Figure 9: load forecasting using NN HL=2, HL=3

Evaluation NN

Total number of instances: 10
Mean squared error: **1059**.8824

Discussions

Figure 5 shows training carried out by time series and regression for many iterations and it showed that the error converges to three which means that there can be an acceptance of ±2 to 4 MW errors in the predicted output for the training dataset.

As shown in table 5 the results for the forecasting year 2016, and it showed that the error converges to three which means that there can be an acceptance in the predicted output for the testing dataset. Figure 6 shows the load curve. The red curve shows the actual load for the year 2006 to 2015 which in keeps in increasing. The blue curve indicates the forecast data for the year 2006 to 2016 and the two green lines indicates the predicted load curve for the year 2016.

The p-value is a number between 0 and 1 and interpreted in the following way:

- A small p-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so you reject the null hypothesis.
- A large p-value (> 0.05) indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis.
- p-values very close to the cutoff (0.05) are considered to be marginal (could go either way). Always report the p-value so your readers can draw their own conclusions.

In the other hand, Table 7 presents the comparison between two model based factors effects. The regression model (OLSR) shows less error rate than other model when using population factors. Moreover, the results for NN compared with time-series regression, the NN where H=2 with nodes 5 better than H=3 with nodes 10, and all prediction it's not capable based on electricity and social factors.

The result of ARIMA regression model used for long- term load forecast for the Gulf Area-Kuwait region shows that the model has a good performance and reasonable prediction accuracy was achieved for this model in the inflected factors.

5. CONCLUSION

In this paper, a soft computing model is introduced, which is integrating the features of data in discovering the most influent factors affecting in load forecasting. Also, introduce a model for load forecasting that takes into consideration the actual factors that affects the electrical usage.

The paper contribution were demonstrates the load forecasting classes and the factors impacting

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its performance especially in Arab Gulf area. The data collected is for the Kuwait Electricity Authority of DC Network for the long-term (10 years) from 2006 to 2015. Classification the Long Term Load Forecasting (LTLF) is a corner stone in using and develop a hierarchal time based load forecasts especially in hot topics like deep learning. Results indicate that this architecture performs quite well when compared to traditional approaches and deep neural network, I case for the p.value and error rate

In order to build a reliable LF system, the reliability and robustness of the system principally rely on the accuracy for forecasts. Weather forecasting, nowadays, reaches a point of accuracy that makes it reliable to be used for VSTLF and STLF.

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