An Approach Towards Real Time Short Term Load Forecasting Using Grey Index Models For Smart Grid Framework

SREENU SREEKUMAR, JATIN VERMA, SUJIL A, RAJESH KUMAR
Malaviya National Institute of Technology
Department of Electrical
Jaipur
India
sreekumarsreenu@gmail.com

Abstract: Short term load forecasting (STLF), which aims to predict system load over an interval of one day or one week, plays a crucial role in the control and scheduling operations of a power system. Most existing techniques on short term load forecasting try to improve the performance by selecting different prediction models. However, the performance also rely heavily on the quality of training data. Although the grey forecasting model has been successfully adopted in various fields and has demonstrated promising results. This paper proposes three short term load forecasting models based on Grey System theory, namely Grey One Index Model (GM(1,1)), Grey Two Index Model using previous year similar day values as input along with previous hour values (GMY (1,2)) and Grey Two Index Model using previous day values as input along with previous hour values (GMD (1,2)) respectively. As shown in the results, the Grey model and its optimized models can increase the existing prediction accuracy. These models have a potential to be used for real time forecasting in smart grid network due to their negligible processing time.

Key–Words: Short Term Load Forecasting, Grey One Index Model, Grey Two Index Model

1 Introduction

Starting from the birth of AC Power Transmission, in 1886 [1], the electrical power system has undergone huge metamorphosis, so much so that in a few years of time it will become ready to transform itself into a Smart Grid system with Artificial Intelligence integrated to govern situational awareness [2]. The basic reason behind this transformation is simple. With the gradual increase in the demand of the most magical, useful and fantastic phenomenon on earth, i.e., electricity, and with inadequate conventional resources to generate electricity, we are left with no other choice but to find alternate ways to tackle out this scarcity. Innumerable approaches spreading from integration of several Renewable Energy Sources (RES) to optimization of energy consumption following various innovative techniques have been proposed, and moreover implemented in order to reduce the consumption of the fuel used for power generation. One of the approaches to optimize the use of fuel at the generation plant is to know exactly the amount of power required to be generated in upcoming time period which will concisely fulfil the demand of consumer side without any fuel wastage. This approach is formally known as Load Forecasting and the behaviour of consumer in terms of load consumption is known to the supplier with the help of historical load consumption data records.

Electric load forecasting is the practice used to forecast upcoming electric load using known historical load and historical, current and forecasted weather information. Load forecasting is normally carried out to help planners in creating strategic decisions with regards to unit commitment, interchange evaluation, hydro-thermal co-ordination and security assessments [3]. Electrical demand forecasting has turned into one of the major research fields in electrical engineering. The supply industry requires forecasts with lead time that ranges from short term to long term. Many countries have recently privatised and deregulated their power systems, and electricity has been turned into a product to be sold and bought at market prices. Since the load forecasts play a crucial role in the structure of these prices, they have become vital for the supply industry [4]. Improvement in accuracy of electric load forecasting model is directly dependent on the cost-effectiveness of the system.

While forecasting load, numerous relative factors have to be considered on which that regional load may depend. Hence, the task becomes a little complicated, because the current hour load may depend on load at previous hours, load at the same hour on the previous days, load in previous weekdays, and so on. Still the load pattern may show some randomness. For achieving further predictability, we may have to consider other features, for e.g. weather-related features, like temperature, humidity, etc. Most of the available and modified models for forecasting purposes have already been tested for Load Forecasting with appreciable success [5]. Broadly, these models are of two types. First one is the Time Series model which models load as a function of its past observations, and second is the Causal model, in which exogenous factors like weather and social variables are also considered as inputs. However, load forecasting can be divided into four major categories [10]:

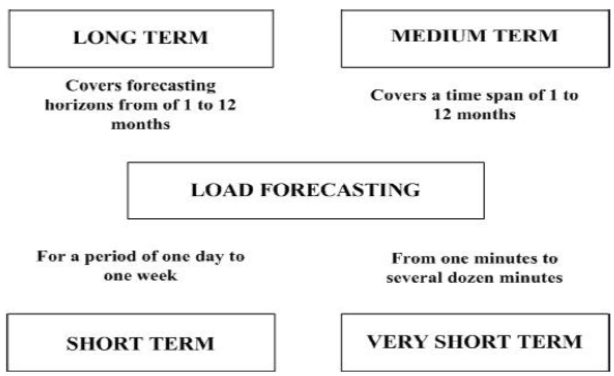

Figure 1: Classification of Load Forecasting

1.1 Long Term Electric Load Forecasting

Forecasting with horizons of one to ten years, and sometimes up to several decades is termed as Long-Term Forecasting. It provides weekly/monthly forecasts for peak and valley loads which are important to expand generation, transmission and distribution systems. In other words, the electric utility company gets to know its future needs such as equipment purchases, staff hiring, expansion and maintenance [6].

1.2 Medium Term Load Forecasting

Medium term load forecasting covers a time span of one to twelve months. This kind of forecasting depends largely on growth factors, i.e. elements that influence demand such as addition of new loads, main events, demand patterns of seasonal variations, large facilities and maintenance requirements of large consumers [7]. Additionally, this kind of forecast uses hourly loads for prediction of the peak loads of days. With this information, it is obvious that whether to take certain amenities/plants for maintenance or not through a given period of time. It will also help in planning major tests and commissioning events. It can also help to decide outage times for plants and major parts of equipment. The estimation methods used for this kind of forecast are similar to that of short term forecast. However, it should be observed that, the sensitivity of medium-term forecasting on power system operations is less than that of the short-term forecasting.

1.3 Short Term Load Forecasting

The short term load forecast is for a period of one day to one week. Short term load forecasting can help in estimating load flows and making decisions that can prevent over loading. Timely implementation of such decisions leads to the improvement of network reliability and reduced occurrences of equipment failures and blackouts. Moreover, short term load forecasting schedules various utility processes like generation, fuel purchases, maintenance and security analysis. Main forecasting errors can lead to either excessive conventional scheduling or excessive risky scheduling that can make heavy economic penalties. Large savings can be attained if exact load forecasts are used to support these actions. The time horizon of the forecast hinge on the way the forecast will be used. Short-term load forecasting (STLF) is necessary for economic scheduling of generation capacity. A very good example about the significance of load forecasting accuracy is that an increase in 1% of forecasting error caused an estimated increase of ten million pounds of operating costs for one electrical utility in United Kingdom [8].

1.4 Very Short Term Load Forecasting

It horizons single minutes to several dozen minutes. With load forecasts having very short time leads, it is easier to monitor the vulnerable varying load-frequency and also economic dispatch functions of the energy management system (EMS). Very short Term Load Forecasting can also fulfil the purpose of real time control and security evaluation [9].

1.5 Importance of Short Term Load Forecasting and Online Application in Smart Grid

Short term load forecasting (STLF) plays a key role in the formulation of reliable, economic and secure operating strategies for the smart power system. The major objective of the STLF function is to provide the load predictions for the elementary generation scheduling functions, evaluating the security of the power system at any time and timely dispatcher information.

The main application of the STLF function is to derive the scheduling functions that determine the most economic commitment of generation sources consistent with operational constraints and policies, reliability requirements, equipment and environmental limitations. For purely hydro systems, the load forecasts are essential for the hydro scheduling function to determine the optimal discharges from the reservoirs and generation levels in the power stations. For purely thermal systems, the load forecasts are required by the unit commitment function to determine the minimal cost hourly strategies for the start-up and shutdown of units to supply the forecast load. For mixed hydro and thermal systems, the load forecasts are needed for hydro-thermal coordination function to plan the hourly operation of the various resources so as to minimize production costs [11-12].

The hydro schedule unit commitment, hydro-thermal coordination function needs system load forecasts for the next day or the next week to determine the least cost operating policies subject to the various constraints imposed on system operation [13]. A closely associated scheduling task is the scheduling and contracting of interchange transactions by the interchange evaluation function. For this function, the short-term load forecasts are also used to determine the economic levels of interchange with other utilities.

A second application of STLF is for predictive assessment of the power system security. The system load forecast is an essential data requirement of the off-line network analysis function for the detection of future conditions under which the power system may be vulnerable. This information permits the dispatchers to prepare the necessary corrective actions to operate the power systems securely. The third application of STLF is to provide system dispatchers with timely information [14].

High penetration of renewable energy sources is one of the major characteristics of smart grid while high intermittency of renewable energy sources makes the scheduling and unit commitment more complex. The effective scheduling for better load-generation balance, real time load forecasting is important. For real time forecasting in smart grid, the net processing time should be less. STLF has significant economic, social and environmental effects, which results into large number of investigation in this field. Large number of techniques are implemented like Fuzzy logic approach [21], Artificial neural networks [7], Bayesian network [22] and classical statistical approaches like Automatic Regression Moving Average (ARMA) [12] etc. In last decades different techniques combined with neural network architectures and support vector regression models are introduced [31-36]. The Neural Network Models are providing comparatively better results, but it requires relatively large amount of training data for more accurate results and there are high chances of overfitting. Therefore the memory requirement and processing time are quite high, due to these problems real time application is difficult with ANN models. So more accurate models having negligible processing time are required, this leads to Support Vector Regression model. The simple SVR models with predefined model paramters have great potential towards online forecasting, but hyper-parameter optimization is time consuming [36]. The above mentioned models require all the correlated factors like temperature, humidity, social and other exogenous factors and large amount of historical data for better accuracy. To avoid these prerequisites, Grey System based prediction is one of the best choices [19],[20]. Grey Index Models are applied when there is no proper information about data sets and its cause factors [30]. The proposed models use only four hour load data as input for the prediction of next hour load.

This paper is further organized as follows: Section 2 defines Grey (1, 1) model and Grey (1, N) model. Section 3 gives data selection for forecasting. Section 4 compare the different forecasted outputs with actual values. Section 5 concludes that GMD (1, 2) gives best performance.

2 GREY MODEL

2.1 Grey One Index Model

GM (1, 1) type of grey model is pronounced as Grey Model First Order One Variable. This model is a time series forecasting model. The differential equations of the GM (1, 1) model have time-varying coefficients. In other words, the model is renewed as the new data become available to the prediction model. The GM (1, 1) model can only be used in positive data sequences [15-18]. In this model, since all the primitive data points are positive, grey models can be used to forecast the future values of the primitive data points. In order to smooth the randomness, the primitive data obtained from the system to form the GM (1, 1) is subjected to an operator, named Accumulating Generation Operator (AGO) (Deng, 1989). The differential equation (i.e. GM (1, 1)) is solved to obtain the n-step ahead predicted value of the system. Finally, using the predicted value, the Inverse Accumulating Generation Operator (IAGO) is applied to find the predicted values of original data [19-21].

Consider a time sequence X^0 that denotes previous day load profile

$$X^0 = (X^0(1), X^0(2), X^0(3), ..., X^0(n)) \quad (1)$$

When this sequence is subjected to the Accumulating Generation Operation (AGO), the following sequence X^1 is obtained. It is obvious that X^1 is monotonically increasing.

$$X^1 = (X^1(1), X^1(2), X^1(3), ..., X^1(n)) \quad (2)$$

where,

$$X^1(k) = \sum_{i=1}^{k} X^0(k) Z^1 X^1 \quad (3)$$

K=1,2,3,4,5..............n

The generated mean sequence Z^1 of X^1 is defined as

$$Z^1 = [Z^1(1), Z^1(2), Z^1(3), ..., Z^1(n)] \quad (4)$$

Where, Z^1 is the mean value of adjacent data.

$$Z^1(k) = 0.5(X^1(k) + X^1(k-1)) \quad (5)$$

The least square estimate sequence of the grey difference equation of GM (1, 1) is defined as follows

$$X^0(k) + aZ^1(k) = b \quad (6)$$

The whitening equation is therefore, as follows

$$\frac{\mathrm{d}}{\mathrm{d}t} X^1(t) + aX^1(t) = b \quad (7)$$

In above, $\begin{bmatrix} a & b \end{bmatrix}^T$ is a sequence of parameters that can be found as follows

$$\begin{bmatrix} a & b \end{bmatrix}^T = \begin{bmatrix} B^T & B \end{bmatrix}^{-1} . B^T . Y \quad (8)$$

Where

$$Y = [x^1(2), x^1(3), ..., x^1(n)]^T \quad (9)$$

$$B = \begin{bmatrix} -Z^1(2) & 1 \\ -Z^1(3) & 1 \\ -Z^1(4) & 1 \\ : & : \\ -Z^1(n) & 1 \end{bmatrix} \quad (10)$$

The solution of $x^1(t)$ at time k is given by

$$X_p^1(k+1) = [X^1(0) - \frac{b}{a}] e^{-ak} + \frac{b}{a} \quad (11)$$

To obtain the predicted value of the primitive data at time (k+ 1), the IAGO is used to establish the following grey model [23-25].

$$X_p^0(k+1) = \left[[X^1(0) - \frac{b}{a}] e^{-ak} + \frac{b}{a} \right] (1 - e^a) \quad (12)$$

2.2 Grey N Index Model

The second index in the GM (1, N) grey model stands for N variables $(X_1^0, X_2^0, ..., X_N^0)$ and the differential equation can be written as follows:

$$\frac{\mathrm{d}X_1^0}{\mathrm{d}t} + aX_1^1 = \sum_{i=2}^{N} b_i - X_i^1 \quad (13)$$

Where $a, b_1, b_2, ..., b_N$ are unknown parameters [20-21]. These parameters can be estimated as follows:

$$\begin{bmatrix} a & b_1 & b_2 & ... & b_N \end{bmatrix}^T = \begin{bmatrix} B^T & B \end{bmatrix}^{-1} . B^T . Y \quad (14)$$

where,

$$Y = [X^1(2), X^1(3), ..., X^1(n)]^T \quad (15)$$

$$B = \begin{bmatrix} -Z^1(2) & X_2^1(2) & ... & X_N^1(2) \\ -Z^1(3) & X_2^1(3) & ... & X_N^1(2) \\ -Z^1(4) & X_2^1(4) & ... & X_N^1(2) \\ : & : & & : \\ -Z^1(n) & X_2^1(n) & ... & X_N^1(2) \end{bmatrix} \quad (16)$$

The forecasts of X_1^1 can be derived by

$$X_p^1(k+1) = (X^1(0) - \sum_{i=2}^{N} \frac{b_{i-1}}{a} X_i^1(k+1)) e^{-ak} + \sum_{i=2}^{N} \frac{b_{i-1}}{a} X_i^1(k+1) \quad (17)$$

To obtain the predicted value of the primitive data at time (k+ 1), the IAGO is used to establish the following grey model [19][23-24].

$$X_p^0(k+1) = \left(\left[X^1(0) - \tfrac{b}{a} \right] e^{-ak} + \tfrac{b}{a} \right) (1 - e^a) \quad (18)$$

3 DATA SELECTION

In this paper, we have selected data from PJM Mid-Atlantic Region[26]. In GM (1,1) model, previous four hour values are used as input and next hour is predicted. In GMY (1,2) model, five hours from previous year similar dayday (which contains the value of corresponding next hour in the previous year) and previous four hour values from the current year are used as input and next hour is predicted. In GMD (1,2) model, five hours from previous day (which contains the value of corresponding next hour) and previous four hour values are used as input and next hour is predicted.

4 RESULTS AND DISCUSSION

The load forecasted by these models were compared to the actual load data and the error was calculated using matlab2014a. The principal statistics used to evaluate the performance of the proposed model are mean absolute percentage error (MAPE) and mean absolute error (MAE). Table II contains MAE and MAPE of different models. Error is calculated by taking the difference between actual value and forecasted value for each data point.

$$E = Y - Q \tag{19}$$

Where Y is actual output, Q is predicted value. Mean Abolute Error is calculated by taking the mean of absolute error.

$$MAE = E_A/N \tag{20}$$

$$E_A = E_1 + E_2 + E_3.....E_N \tag{21}$$

Where $E_1, E_2, E_3, ...E_N$ are absolute values of individual errors. Percentage error is calculated by dividing absolute value of error by corresponding actual value.

Mean Absolute Percentage Error is the mean of absolute percentage error

$$MAPE = (1/N)\sum|PE| \tag{22}$$

Table 1: MAE of GM (1,1), GMY(1,2) and GMD (1,2) models for different days

Days	MAE (kW)		
	GM (1,1)	GMY (1,2)	GMD (1,2)
January 20	699.01	633.96	240.88
February 20	1160.6	560.3	301.19
March 24	748.19	829.27	696.97
April 24	978	229.68	246.05
May 26	531.88	781.75	261.25
June 27	1294	1711.2	463.66
July 28	704.4	710.78	305.92
August 29	982.32	440.36	905.19
September 28	666.09	737.53	560.76
October 27	710.03	391.73	494.98
November 29	857.2	451.84	692.53
December 31	980.18	325.91	564.81

One of the main factors affecting load consumption profile of mid atlantic region is temperature [29]. We have considered average monthly temperature data for discussing the predicted load consumption pattern from US climatic data center [28]. The months January, February, March, April, October, November

Table 2: MAPE of GM (1,1), GMY(1,2) and GMD (1,2) models for different days

Days	MAPE (%)		
	GM (1,1)	GMY (1,2)	GMD (1,2)
January 20	2.34	2.26	0.85
February 20	3.22	1.51	0.80
March 24	2.56	2.84	2.39
April 24	3.59	0.82	0.86
May 26	2.30	3.31	1.17
June 27	3.61	4.81	1.16
July 28	2.25	2.29	1.01
August 29	2.88	1.29	2.54
September 28	2.73	3.10	2.37
October 27	2.73	1.51	2.01
November 29	2.66	1.42	2.15
December 31	2.80	0.93	1.62

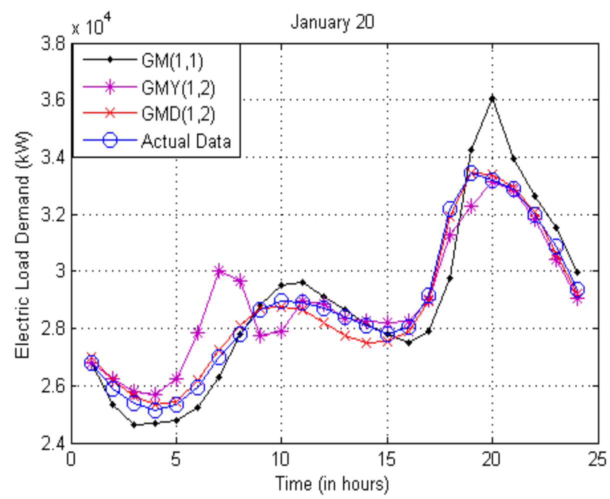

Figure 2: Performance plot of January 20.

and December have temperature ranging from -4 to 20 degree celsius. This range corresponds to cool weather, thus electric load demand increases in the form of heating load, for e.g. heaters, geysers, etc, and therefore overall load consumption is higher as is evident from figures of corresponding months. Rest of the months have moderate weather. July and August are the hottest months with temperature reaching upto 31 degree Celsius, which again increases electric load demand in the form of cooling load, for e.g. coolers, ACs, etc. and hence their peak loads are higher than other months; the same can be seen in the corresponding Figures. Figure 2, Figure 3, Figure 4, Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, Figure 12 and Figure 13 show the performance plots of January 20, February 20, March 24, April 24, May 26, June 27, July 28, August 29, September 28, October 27, November 29 and December 31. Table I and Table II shows MAE and MAPE of different models for different days. The average values of Mean Absolute Error, Mean Absolute Percentage Error and Maximum Error of GM (1,1), GMY (1,2) and GMD (1,2) are 859.32 kW, 2.80 % and 8.74 %, 650.35 kW, 2.17 % and 11.44 %, 477.84 kW, 1.58 % and 6.18 % respectievely. MAPE is reduced by 28.89% from GM (1,1) to GMY (1,2) and by 77.84% from GM (1,1) to GMD (1,2). The performance plots show that GMY (1,2) possess some abnormal points, this is due to the large difference in data between two years at some points. Out of three models, GMD (1,2) shows better results, MAPE is only about 1.58%. The performance parameters of the best model (GMD (1,2)) are compared with SVRGA model proposed by the authors in [37]. MAPE is reduced by 27.52 % from SVRGA TO GMD (1,2).

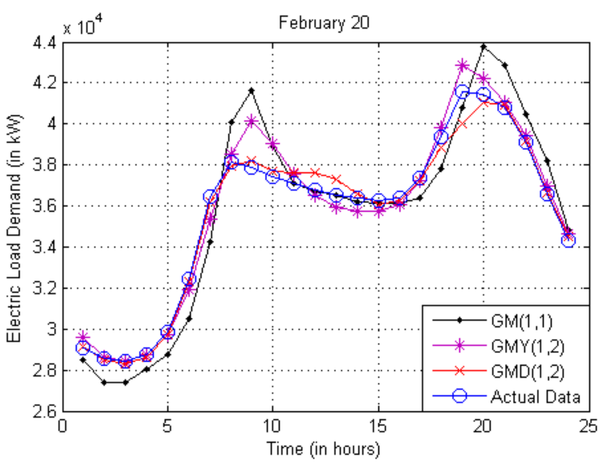

Figure 3: Performance plot of February 20

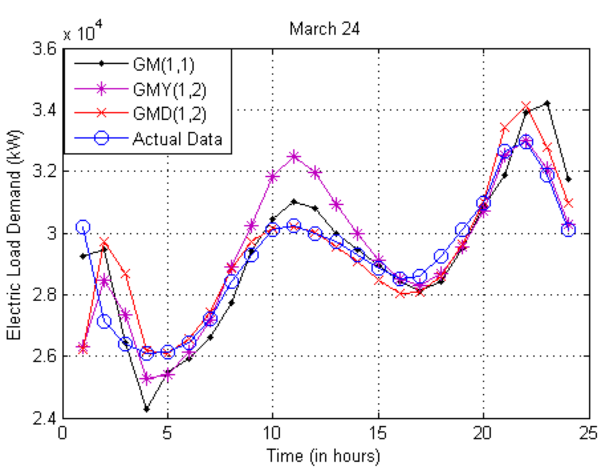

Figure 4: Performance plot of March 24

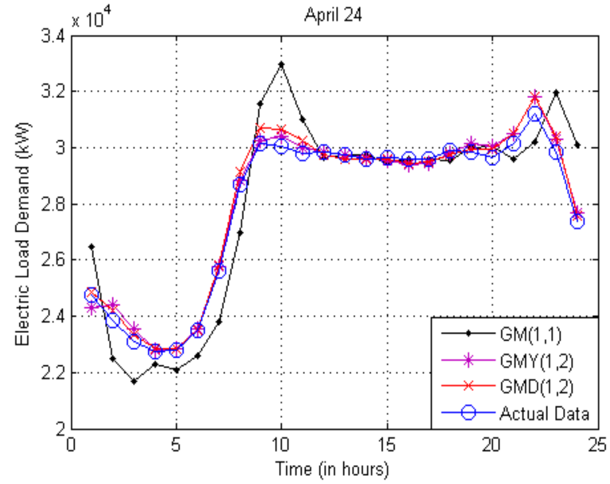

Figure 5: Performance plot of April 24

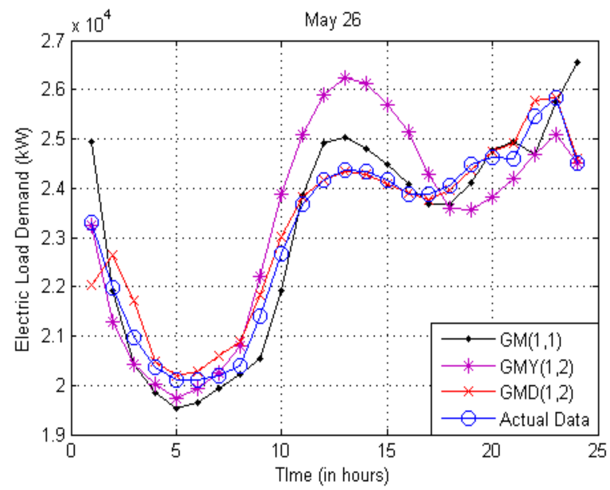

Figure 6: Performance plot of May 26

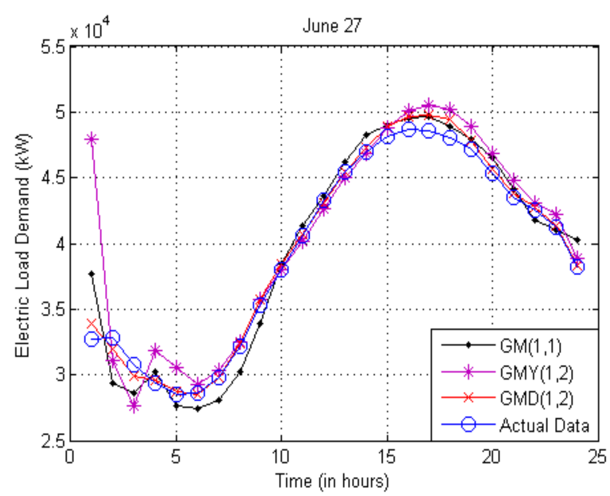

Figure 7: Performance plot of June 27

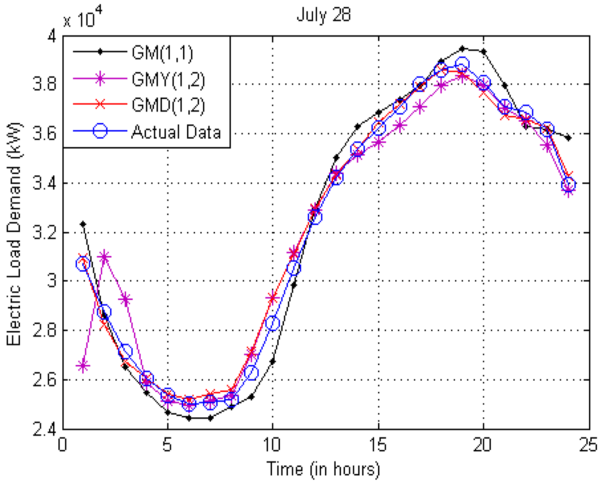

Figure 8: Performance plot of July 28

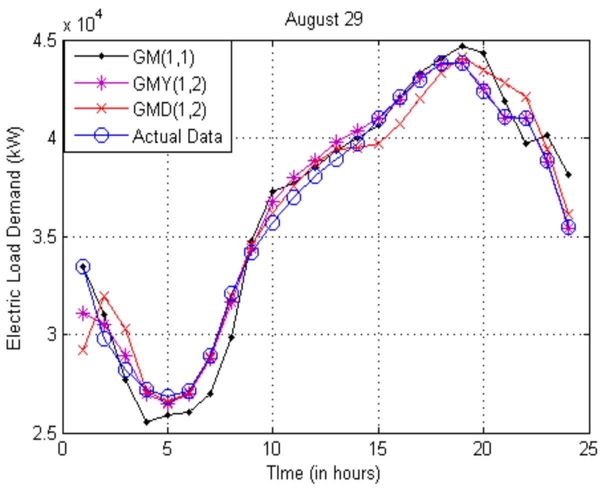

Figure 9: Performance plot of August 29

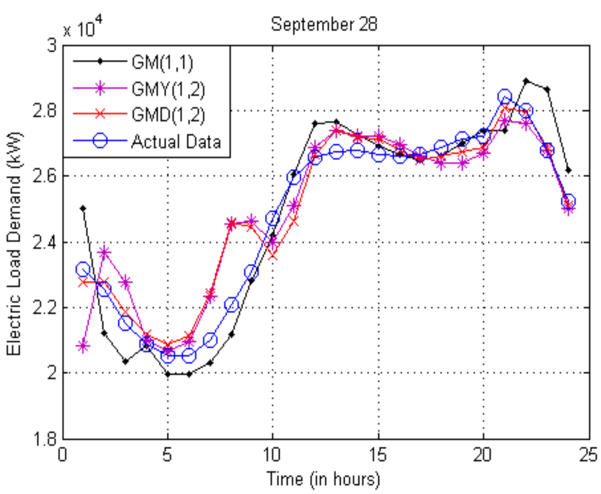

Figure 10: Performance plot of September 28

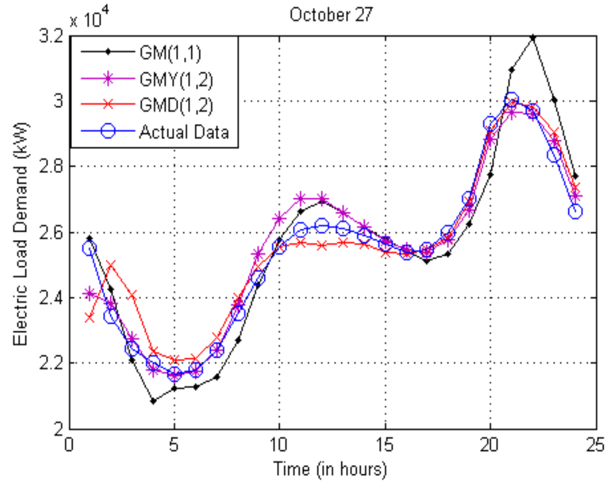

Figure 11: Performance plot of October 27

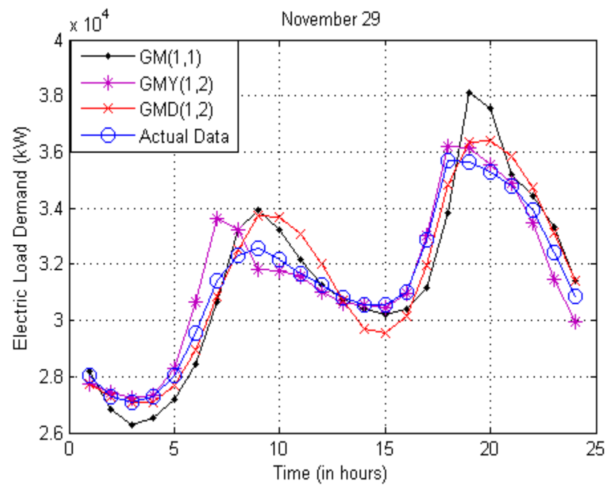

Figure 12: Performance plot of November 29

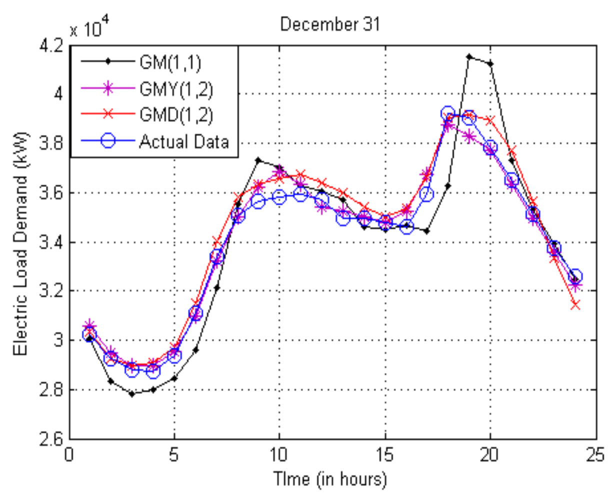

Figure 13: Performance plot of December 31

5 CONCLUSION

There is a major economical inspiration for improving the accuracy of electrical load forecasting. Efficient load forecasting methods are very helpful for unit commitment, hydrothermal scheduling, inter change evaluation and security assessments. In the past, various load forecasting methods have been developed for the short term load prediction problems. However, very few scholars tried to introduce the Grey model.The Grey Index Models requires only small amount of data, here only 9 data points are used as input. This leads to less memory requirement and fast operation. Grey Index Models have great accuracy level with only negligible processing time, so we can use these models in real time forecasting in smart grid network. Thus, the authors developed a pilot study for predicting the hourly load using the data being measured in previous hours, previous year similar day values and previous day values and got satisfactory forecasting results. There is 28.89% reduction in MAPE from GM (1, 1) model to GMY (1, 2) model and 77.84 % reducction in MAPE from GM (1,1) to GMD (1,2) which shows different features have different effect on forecasting accuracy. Out of these three model GMD (1,2) has highest accuracy of 98.42%. The grey model can be used for real time forecasting in the areas where large amount of data and the factors affecting load are not known. We can further improve the accuracy by the addition of exoegenous factors.

References:

[1] N. Rajkumar *"Direct current and alternating current systems "*, Electrical Engineering Vol. I, Encyclopedia of Life Support Systems (EOLSS), 2011.

[2] Gungor, Vehbi C., Dilan Sahin, Taskin Kocak, Salih Ergut, Concettina Buccella, Carlo Cecati, and Gerhard P. Hancke*"Smart grid technologies: communication technologies and standards"*, IEEE transactions on industrial informatics 7 , no. 4, pp:529-539,2011.

[3] Park, Dong C., M. A. El-Sharkawi, R. J. Marks, L. E. Atlas, and M. J. Damborg *"Electric load forecasting using an artificial neural network"*, IEEE transactions on power systems 6,no.2, pp: 442-449,1991.

[4] Metaxiotis, K., A. Kagiannas, D. Askounis, and J. Psarras*"Artificial intelligence in short term electric load forecasting: a state-of-the-art survey for the researcher"*, Energy Conversion and Management 44, no. 9 pp: 1525-1534,2003.

[5] Chen, Bo-Juen, Ming-Wei Chang, and Chih-Jen Lin*"Load forecasting using support vector machines: A study on EUNITE competition 2001"*, IEEE Transactions on power systems 19, no. 4 , pp: 1821-1830,2004.

[6] Carpinteiro, Otavio AS, Rafael C. Leme, Antonio C. Zambroni de Souza, Carlos AM Pinheiro, and Edmilson M. Moreira *"Long-term load forecasting via a hierarchical neural model with time integrators"*, Electric Power Systems Research 77, no. 3, pp: 371-378,2007.

[7] Yalcinoz, T., and U. Eminoglu *"Short term and medium term power distribution load forecasting by neural networks"*, Energy Conversion and Management 46, no. 9 ,pp: 1393-1405,2005.

[8] Shahidehpour, M.,Yamin, H. Li,Z *"Short term Load forecasting"*, Market operations in electric power systems :forecasting, scheduling and risk managment, pp:21-56, 2002.

[9] Liu, K., S. Subbarayan, R. R. Shoults, M. T. Manry, C. Kwan, F. L. Lewis, and J. Naccarino*"Comparison of very short-term load forecasting techniques "*, IEEE Transactions on power systems 11, no. 2 ,pp: 877-882,1996.

[10] Feinberg, Eugene A., and Dora Genethliou *"Load forecasting"*, In Applied mathematics for restructured electric power systems, Springer US,pp.269-285,2005.

[11] Reis, AJ Rocha, and A. P. Alves da Silva *"Feature extraction via multiresolution analysis for short-term load forecasting"*, IEEE Transactions on power systems 20, no. 1, pp: 189-198,2005.

[12] Huang, Shyh-Jier, and Kuang-Rong Shih *"Short-term load forecasting via ARMA model identification including non-Gaussian process considerations"*, IEEE Transactions on power systems 18, no. 2, pp: 673-679,2003.

[13] Amjady, Nima *"Short-term hourly load forecasting using time-series modeling with peak load estimation capability"*, IEEE Transactions on power systems 5, no. 4 ,pp: 1535-1547,1990.

[14] Papalexopoulos, Alex D., and Timothy C. Hesterberg *"A regression-based approach to short-term system load forecasting"*, IEEE Transactions on power systems 16, no. 3,pp: 498-505,2001.

[15] Wu, Wann-Yih, and Shuo-Pei Chen. *"A prediction method using the grey model GMC (1, n) combined with the grey relational analysis: a case study on Internet access population forecast."*, Applied Mathematics and Computation 169, no. 1, pp: 198-217, 2005.

[16] Wang, Mang-Hui, and Chin-Pao Hung. *"Novel grey model for the prediction of trend of dissolved gases in oil-filled power apparatus."*, Electric Power Systems Research 67, no. 1 pp:53-58, 2003.

[17] Hsu, Li-Chang. *"Applying the grey prediction model to the global integrated circuit industry."*, Technological Forecasting and Social Change 70, no. 6, pp: 563-574,2003.

[18] Wen, Kun-Li. *"Grey systems: modeling and prediction."*, Yang's Scientific Research Institute, 2004.

[19] Kayacan, Erdal, Baris Ulutas, and Okyay Kaynak. *"Grey system theory-based models in time series prediction."*, Expert Systems with Applications 37, no. 2,pp:1784-1789,2010.

[20] Lee, Yi-Shian, and Lee-Ing Tong. *"Forecasting energy consumption using a grey model improved by incorporating genetic programming."*, Energy conversion and Management 52, no. 1, pp: 147-152, 2011.

[21] Bakirtzis, A. G., J. B. Theocharis, S. J. Kiartzis, and K. J. Satsios *"Short term load forecasting using fuzzy neural networks"*, IEEE Transactions on power systems 10, no. 3, pp: 1518-1524,1995.

[22] Lauret, Philippe, Eric Fock, Rija N. Randrianarivony, and Jean-Francois Manicom-Ramsamy *"Bayesian neural network approach to short time load forecasting"*, Energy conversion and management 49, no. 5, pp: 1156-1166,2008.

[23] Akay, Diyar, and Mehmet Atak. *"Grey prediction with rolling mechanism for electricity demand forecasting of Turkey."*, Energy 32, no. 9,pp: 1670-1675, 2007.

[24] Zhou, P., B. W. Ang, and K. L. Poh. *"A trigonometric grey prediction approach to forecasting electricity demand."*, Energy 31, no. 14 ,pp: 2839-2847,2006.

[25] El-Fouly, T. H. M., E. F. El-Saadany, and M. M. A. Salama. *"Grey predictor for wind energy conversion systems output power prediction."*, Power Systems, IEEE Transactions on 21, no. 3,pp: 1450-1452,2006.

[26] Ji, P. R., W. S. Huang, and X. Y. Hu. *"A study on the properties of grey forecasting model."*, Systems Engineering Theory and Practice 9,pp: 105-108, 2001.

[27] Li, Jun-Fang, Bu-Han Zhang, Guang-Long Xie, Yan Li, and Cheng-Xiong Mao. *"Grey predictor models for wind speed-wind power prediction."*, Power System Protection and Control 38, no. 19,pp: 151-159, 2010.

[28] Data source: http://www.pjm.com/markets-and-operations/energy/real-time/loadhryr.aspx.

[29] Data source: http://www.usclimatedata.com /climate/philadelphia/pennsylvania/united-states/uspa1276/2015/1.

[30] Deng Julong *"Introduction to Grey System Theory"*, The Journal of Grey System, vol 1,pp: 1-24, 1989.

[31] Wei-Chiang Hong. *"Electric load forecasting by support vector model"*, Applied Mathematical Modelling 33.pp: 24442454, 2009.

[32] Zhongyi Hu, Yukun Bao, and Tao Xiong *"Electricity Load Forecasting Using Support Vector Regression with Memetic Algorithms"*, Hindawi Publishing CorporationThe Scientific World Journal Volume 2013, Article ID 292575.

[33] Zeng, Jianwu, and Wei Qiao *"Support vector machine-based short-term wind power forecasting"*, In Power Systems Conference and Exposition (PSCE), 2011 IEEE/PES, pp. 1-8. IEEE, 2011.

[34] Elattar, Ehab E., John Goulermas, and Q. Henry Wu *"Electric load forecasting based on locally weighted support vector regression"*, In Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on 40, no. 4, 438-447, 2010.

[35] Okasha, Mahmoud K *"Using Support Vector Machines in Financial Time Series Forecasting"*, In International Journal of Statistics and Applications, 4(1), pp: 28-39, 2014.

[36] Sreenu Sreekumar, Jatin Verma, Sujil A, Rajesh Kumar *"One Day Ahead Prediction of Hourly Electrical Load using Genetically Tuned Support Vector Regression for Smart Grid Frame Work"*, In IEEE Conference on Recent advances in engineering and computational Sciences (RAECS 2015, 21-22 December), 978-1-4673-8253-3/15/31.00 2015 IEEE.