

## A Review of Conventional, Modern and Big Data Analytics Techniques for Short Term Load Forecasting in Smart Grid

<sup>1</sup>Firoz Mohammed, <sup>2</sup>Kamlesh Gupta, <sup>3</sup>Namrata Nebhnani, <sup>4</sup>Priya Pal

<sup>1</sup>Assistant Professor, Department of Electrical & Electronics Engineering, IPS Academy, Institute of Engineering and Science, Indore

<sup>2</sup>Assistant Professor, Department of Electrical & Electronics Engineering, IPS Academy, Institute of Engineering and Science, Indore

<sup>3</sup>Assistant Professor, Department of Electrical & Electronics Engineering, IPS Academy, Institute of Engineering and Science, Indore

<sup>4</sup>Assistant Professor, Department of Electrical & Electronics Engineering, IPS Academy, Institute of Engineering and Science, Indore

**Abstract:** Electric load forecasting is a very important part of smart grids. With the help of short term load forecasting, electric load from half an hour's to several hours can be predicted. This paper is focused on full comparison among the different techniques of electric load forecasting considering change in trend and values under diverse situations using latest non analytical soft computing techniques which affects short term electric load forecasting. This paper also depicts the changing latest trend in Electric load forecasting from conventional to the modern techniques like Artificial intelligent along with Big Data Analytics for Short term load forecasting in very simple and efficient way.

**Keywords:** Load Forecasting, Artificial intelligent, Big Data, Data Analytics.

### INTRODUCTION

For smooth working of an electric utility like fuel resources scheduling and making premeditated & correct decisions for balancing the electric supply and load demand are regulated by electric load forecasts. During the revolution of electricity market, electric load forecasts acquired lot of attention across other business area like energy trading, financial planning etc. Precise load forecast are the essential requirement for spot price concern for the utility to achieve the lowest amount of electricity purchasing cost in the electric market environment. There is a great interest is being observed by the utility in smart grid implementations, load forecasting has greater importance due to its wide applications in the forecast of demand side management, planning for storage maintenance and scheduling, renewable energy sources integration etc. It also helps to electric consumer for understanding the correlation between the load demand and cost of electricity varying the electricity usage pattern according to the price. Now power system management is getting updated in terms of smart grid, which involves computer based relaying system to convert existing network in more reliable and capable practical application. The existing conventional system incapable of managing various network issue like system stability, peak load management, reliability and deregulation of power etc. The existing conventional system can be transformed to smart operations by integrating above parameters. The prime objective of smart grid network is to

enhance and advance the reliability and flexibility of existing power system in cost effective manner.

## LOAD FORECASTING

Electricity Load Forecasting is a central and integral process for planning periodical operations and facility expansion in the electricity sector. Accurate forecasts lead to substantial savings in operating and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development. Precise models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development.

**Factor Affecting Electricity Load Forecasting:** There are several factors that should be taken into consideration for load forecasting, which can be classified as[21] :

**i. Time factor:** The time 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. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence.

**ii. Economic factor:** The load pattern is also function of economic factors such as industrial development, population growth, Gross Domestic Product (GDP) and cost of electricity etc. Long-term load forecasting significantly affected by economic factors, however it is also important for medium-term and short-term forecasting. According to the different horizons of forecasting, the different economic factors could contribute to e.g. time-of-use for short-term forecasting, purchasing power for medium term forecasting, and GDP for long-term forecasting etc.

**iii. Weather data factor:** Various weather variables could be considered for load forecasting are **temperature, humidity, wind speed and cloud cover.**

- **Temperature:** Most of activities currently involve consumption of electricity. Load and temperature are linked to some level. There is a positive correlating contribution between temperature and electric load curve especially in summer season [21]. This is because during summer change in temperature will affect the people's feeling of comfort level requirement. During summer as the temperature rises, the increased usage of cooling appliances also increases the load consumption, whereas the temperature fall in the winter season, the more usage of heating appliances would increase the load consumption.
- **Humidity:** Humidity affects short term load forecasting since it increases the feeling of severity of temperature during summer and rainy season. Thus, load consumption increases during summer humid day.

- **Wind speed:** Wind speeds effect the electricity load consumption. During the windy day human body feels the temperature far below and heating appliance is required thus increasing the load consumption.
- **Cloud cover:** The effects of cloud cover on the usage of electricity depend on the timings of usage. During day time the cloud cover may disturb the sunlight, results decrease in the temperature and hence lower the usage of electricity consumption

**iv. Customers' classes factor:** The load shape may be different for different customer classes. Most electric utilities serve customers of different types as residential consumer, commercial consumer and industrial consumer. The customer factors of electricity consumption are primarily the number, type and size of the electrical equipment of the customer. While the electrical equipment and installations vary from customer to customer. There are recognized types of customers which have similar properties. The residential load curve is somewhat different from commercial and industrial customers.

### Classification of Load Forecasting

Load forecasting is essential for planning and operational decision making. Based on the time horizon or lead time, load forecasting can be categorized in three major groups. The differences in time horizon have consequences for the models and methods applied and for the input data available and selected. The decision maker must consider not only finding the appropriate model type but also determining the important external factors needed to get the most accurate forecast [25].

**Table 2: Categorization of Load Forecasting**

S. No.	Nature of Forecast	Lead time	Applications
1	Very short term	Few seconds to few minutes	Scheduling of generation and distribution, power system security analysis
2	Short term	Half an hour to the number of hours	It uses in study of economics dispatch, unit commitment, hydro-thermal coordination, load flow analysis and security studies [27].
3	Medium term	Few days to a number of weeks	Planning for seasonal peak winter, summer & as its application is in maintenance schedule
4	Long-term	Up to one year	Planning generation growth [25].

### SIGNIFICANCE OF SHORT TERM LOAD FORECASTING (STLF)

Short term load forecasting (STLF) is an essential part of daily operations of the utilities. No utility is able to work without it. Moreover, nowadays, STLF has become an urgent matter due to the complexity of loads, the system requirements, the stricter power quality requirements, and deregulation. The error in forecasting would lead to increased operational cost and decreased revenue. In the deregulation issue, STLF is going to be of benefit in determining the schedule of energy transactions, preparing operational plans and bidding strategies. STLF provides the input data for load flow studies and contingency analysis in case of loss of generator or of line.

STLF would be useful for utility engineers in preparing the corrective plan for the different types of expected faults. STLF is involved in a number of key elements that ensure reliability, security and economic operation of power systems. Gross and Galiana [26] stated the principal objective of the STLF is to provide the load prediction for:

1. The basic generation scheduling function to determine the most economic commitment of generation sources consistent with reliability requirements, operational constraints and policies, and physical, environmental, and equipment limitations

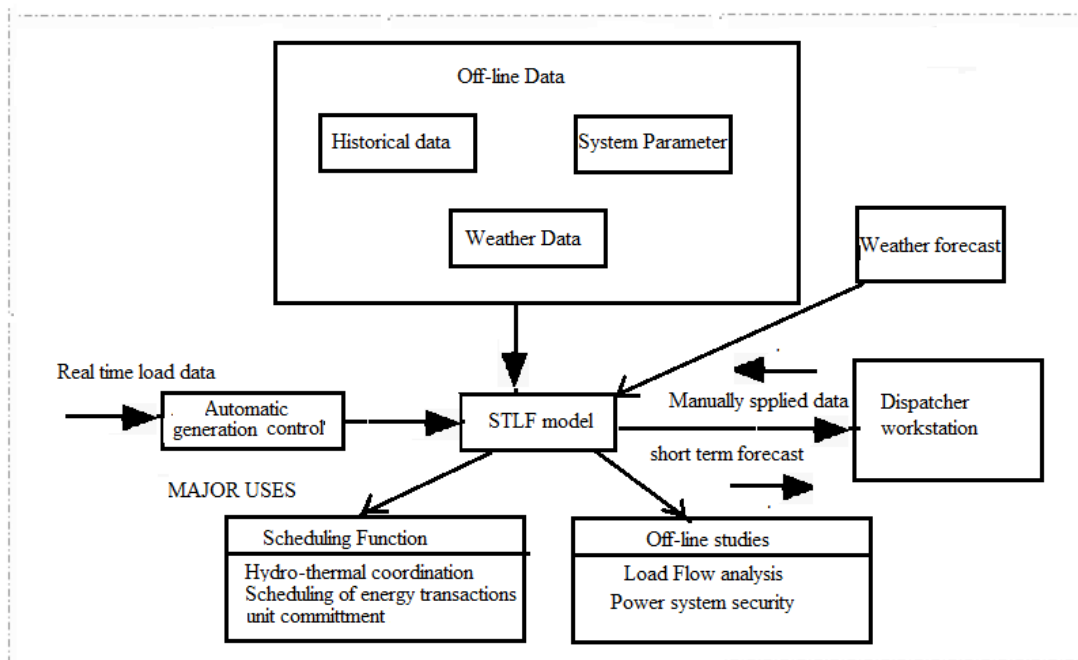


Figure 1: An Input-Output Configuration of A STLF System and Its Major Uses [26]

2. Assessing the security of the power system at any time point, especially to know in which condition the power system may be vulnerable so the dispatchers can prepare the necessary corrective actions such as switching operations, power purchases to operate the systems securely
3. Timely dispatcher information to operate the system economically and reliably.

To achieve those objectives, some major components are needed. The major components of an STLF system are the STLF model, the data sources, and the man-machine interface. Fig. 1 shows a general input-output configuration of an STLF system and its major uses.

**SHORT TERM LOAD FORECASTING METHODS**

There are various approaches to short term load forecasting, which can be classified into two main categories first is conventional or classical approaches and second is modern approaches:

- Similar Day Approach,
- Various Regression Models,
- Time Series,
- Neural Networks,
- Expert Systems,
- Fuzzy Logic, And Statistical Learning Algorithms

A comparative analysis of different techniques for STLF is shown in table 2 along with specific model , strength and weakness . This comparative analysis is very useful for selection of load forecasting technique with higher accuracy in predication of electric load.

**Table 2: Comparison of Different Techniques for Short Term Load Forecasting**

Load Forecasting Techniques	Specific Model Used	Strength	Weakness
<b>Regression</b>	I. Linear Regression and II. Multiple Linear Regression	<ul style="list-style-type: none"> <li>➤ Very useful in non-real time forecasting.</li> <li>➤ Functional relationship between previous, forecast load and other factors such as weather, time of the day.</li> </ul>	<ul style="list-style-type: none"> <li>➤ Not accurate for real time load and</li> <li>➤ Unable to handle nonlinear load consumption.</li> </ul> Adding parameters make it unstable.
<b>Time-series Analysis</b>	I. Auto Regressive Moving Average, II. Auto Regressive Integrated Moving	They Possess abilities to accommodate seasonal component effects.	They suffer numerical instability

	Average, III. Deterministic decomposition.		
<b>Artificial Neural Network</b>	I. Multiplayer Perceptrons, II. Back Propagation Algorithm, III. Steepest descent Error Back Propagation	Ability to handle nonlinear relationships in load consumption by adjusting its weight during the training process.	Large amounts of data are needed to train the model and complexity in the training of such data.
<b>Fuzzy Inference System</b>	I. Defuzzification Method using Centre of Area, II. Middle of Maxima, III. Last of Maxima and Centre of gravity	Faster and more accurate in performance including simplicity in rule formation.	Selection of membership function to form its rule is based on trial and error.
<b>Support Vector Machine</b>	I. Support Vector Regression using Incremental Learning Algorithm, II. Support Vector Regression	It enhances higher feature space dimensionality by using $\epsilon$ - insensitive loss for linear regression computation and reduction in model complexity.	Choosing of suitable Kernel and difficulties in its interpretation are major concerns

After analysis of different STLF techniques it is clear that conventional method like Regression and Time Series analysis is capable to deal only linear load forecast and they suffer numerical instability. While Modern techniques like Artificial Neural Network and Fuzzy Inference System techniques have ability to handle nonlinear relationships in load consumption by adjusting its weight during the training process of data. Fuzzy Inference System has faster and more accurate in performance including simplicity in rule formation.

## BIG DATA ANALYTICS AND TECHNOLOGY

The term Big Data is generally used to refer to a massive amount of data with specific complexities, the so-called 4Vs: **Volume** : refers to the scale of the data when the amount of data reaches almost incomprehensible proportions. **Variety** : refers to the data being heterogeneous: data that comes from different sources which represent differences in type,

format, volume and so forth. **Velocity** : refers to how fast the data is coming in, but also to how fast an analytic method needs to be able to analyze and utilize the data. **Veracity** : in data deals with the trust worthiness or usefulness of results obtained from data analysis, which plays a profound role for decision making [47].

BIG DATA Technology is a new scientific trend [48], [49]. Driven by data analysis in high-dimension, big data technology works out data correlations to gain insight to the inherent mechanisms. Data driven results only rely on an unrestrained selection of system raw data (the space can be whole system or only a region, the time can be long or short, and the size can be large or small) and a general statistical procedure (for data processing). One underlying issue that makes it particularly difficult to delineate what constitutes big data analytics is the volume of data being considered in electricity grid applications today, which typically is at the terabyte scale, far from the peta byte scale that is considered as big data in some other domains. Finally, the concept of “data analytics” is also a bit misleading since most of the traditional applications in the electricity grid domain are based on the processing of measurement data, which may or may not be considered as data analytics in a big data context. As an example, the traditional approaches to state estimation and fault location would not necessarily qualify as big data analytics if they are only based on mathematical equations derived from physics. On the other hand, fault prediction based on data-driven models utilizing high resolution weather and outage data may qualify for big data analytics.

## **BIG DATA IN THE SMART GRID**

Smart meters are replacing existing electricity meters which provide energy consumption data to the energy suppliers automatically with higher time resolution. Phasor Measurement Units (PMUs) are typically applied, at transmission level, which help system operator to become aware of the situation of whole system, by measuring in many different locations of the system. Since power quality is a critical aspects of the reliability as perceived by the end user, a large number of power quality monitoring devices has been installed in different locations in the smart grid. In addition to these electrical sources of data there are other types of data in the smart grid such as Data from energy market pricing and bidding; Data from management, control and maintenance of devices and equipment in the electric power generation, transmission and distribution parts of the grid; and Data from operating utilities, like large data sets which are not directly obtained through measurements in the network [51].

**The Key Technologies Of Electric Power Big Data System:** The integration and management technologies of electric power big data include data fusion and data integration, database management technology, Extract-Transform-Load (ETL) technology, which is shown in Figure 2.

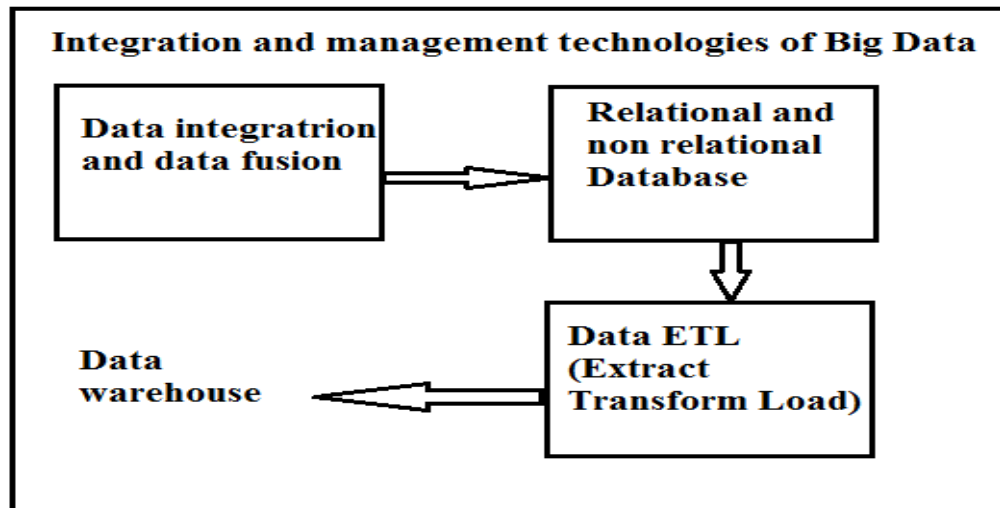


Figure 2: Integration and management technologies of electric power big data

## PROPOSED METHODOLOGY

**Time Series method:** A Time Series is a time-oriented or chronological sequence of observations on a variable of interest [54]. Decomposition is used in time series to describe the trend and seasonal factors in a time series. There are several types of adjustments or components that are useful in time series modeling and forecasting such as prior monthly (Pt), trading day (Dt), trend (Tt), seasonality (St), and irregularity (It) [55]. These components could be added (additive) or multiplied (multiplicative) to constitute the time series. The multiplicative decomposition can be represented [55]:

$$Y_{mt} = Pt * Dt * Tt * St * It$$

where  $Y_{mt}$  denotes multiplicative time series

**Artificial Neural Network :** Artificial Neural Network (ANN) is network of interconnected small computational units called neurons, inspired by biological neurons. Equation of multi layer perceptron (shown in Fig. 3) neural networks is given below:

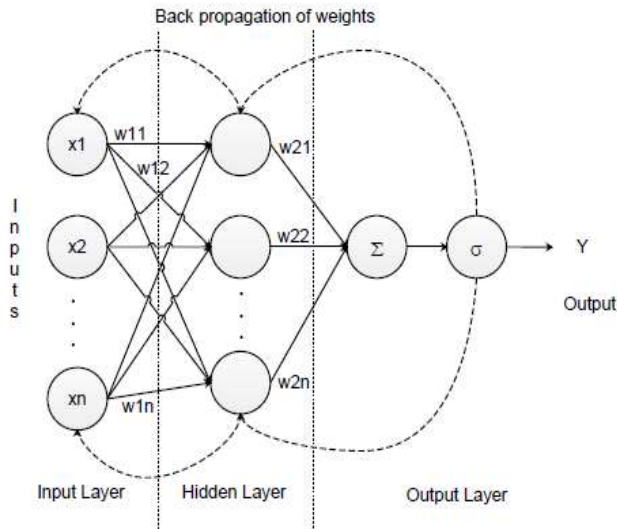


Figure 3: Simplest ANN: multilayer perceptron with back propagation of weights.

$$y(x_1, \dots, x_n) = f(w_0 + w_1x_1 + \dots + w_nx_n)$$

Where,  $x_i$  are the inputs,  $f(v)$  is input to output mapping function,  $w_i$  are the weights and  $w_0$  is the bias. The function is given by following equation:

$$f(v) = \frac{1}{1 + e^{-v}}$$

The output activation function can be written as following that is a simple binary discrimination (zero-centered) sigmoid:

$$f(v) = \frac{1 - e^{-v}}{1 + e^{-v}}$$

ANN models can be used for prediction of both time series and multivariate inputs [56].

**Neo4j graph database:** Big Data can bring a good performance improvement by leading to more effective and better decision making and optimizing business process. With analytical tools these types of data enable better prediction of future activity and performance, such as load forecasting, and allow organizations to adjust processes to achieve better outcomes. A range of new technologies such as NotOnly SQL (NoSQL) have emerged to deal with technical aspect of processing and managing of large amounts of data that are generated fast and from various sources[9].

## CONCLUSION

The short term load forecasting is important for proper planning, operation and maintenance in power transmission system. The ability to capture, collect and store huge amounts of data such as consumption and weather's conditions data and other Big Data, using sensors technology advances, leads to new insights and better making decision. A methodology for short term load forecasting is proposed which is created by using graph technology - Neo4j, as Big Data NoSQL data store, to process, store and analyze those large amounts of data and compare with Artificial Neural Network (ANN)& Time Series method.

## REFERENCES

- [1] Changhao Xia, Jian Wang, Karen McMenemy, "Short, medium and long term load forecasting model and virtual load forecaster based on radial basis function neural networks", Elsevier, Electrical Power and Energy Systems 32 (2010) 743–750
- [2] Engr. Badar Ul Islam, "Comparison of conventional and modern load forecasting technique based on Artificial Intelligence and Expert system", IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 5, No 3, September 2011 ISSN (Online): 1694-0814
- [3] Shahida Khatoun, Ibraheem, Arunesh Kr. Singh, Priti, "Analysis and Comparison of Various Methods Available for Load Forecasting: An Overview", International Conference on Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH14) 28 & 29 November 2014.
- [4] Swapnendra Singh Chauhan, Praveen Bansal, Neetu Agarwal, "Comparative Study of Load Forecasting Methodologies in Electrical Power System", INTERNATIONAL JOURNAL OF SCIENTIFIC PROGRESS AND RESEARCH (IJSPR) ISSN: 2349-4689 Volume-12, Number - 03, 2015.
- [5] N. Phuangpornpitak and W. Prommee, "A Study of Load Demand Forecasting Models in Electric Power System Operation and Planning", GMSARN International Journal 10 (2016) 19 – 24
- [6] Kumar Reddy Cheepati and T. Nageswara Prasad, "Performance Comparison of Short Term Load Forecasting Techniques", International Journal of Grid and Distributed Computing Vol. 9, No. 4 (2016), pp.287-302
- [7] Kuldeep S & Dr. Anitha GS, "Short Term Load Forecasting Methods, A Comparative Study", IJARIIIE-ISSN (O)-2395-4396,C-1400, Vol-1 Issue-5 2016
- [8] Huifang Li, Yidong Li, Hairong Dong, "A Comprehensive Learning-Based Model For Power Load Forecasting In Smart Grid", Computing and Informatics, Vol. 36, 2017, 470 {492, doi: 10.4149/ cai 2017 2 470}
- [9] Daniela Minkovskab, Lyudmila Stoyanovac , Arbër Perçukua, "Big Data And Time Series Use In Short Term Load Forecasting In Power Transmission System", Science Direct Computer Science 141 (2018) 167–174
- [10] Jie Zhan, Jinxin Huang, Lin Niu , "Study of the key technologies of electric power big data and its application prospects in smart grid", Huazhong University of Science and Technology

Wuhan, China Email: [XiaoshengPeng@hust.edu.cn](mailto:XiaoshengPeng@hust.edu.cn). 978-1-4799-7537-2/14/\$31.00 ©2014 IEEE

[11] Claudio Inácio de Almeida Costa, Luiz Eduardo Borges da Silva, “*Big Data Techniques applied to Load Forecasting*”, <https://www.researchgate.net/publication/289117292>, 2015

[12] Azam Bagheri Math H.J. Bollen “*Big Data from Smart Grids*”, Department of Electrical Engineering Luleå, University of Technology Skellefteå, 978-1-5386-1953-7/17/\$31.00 ©2017 IEEE

[13] Heng Shi, Minghao Xu, and Ran Li, “*Deep Learning for Household Load Forecasting—A Novel Pooling Deep RNN*”, IEEE TRANSACTIONS ON SMART GRID, VOL. 9, NO. 5, SEPTEMBER 2018 IEEE

[14] Arber Perçuku, Daniela Minkovska, Lyudmila Stoyanova, “*Big Data And Time Series Use In Short Term Load Forecasting In Power Transmission System*”, *Procedia Computer Science* 141 (2018) 167–174 [toyanova/Procedia Computer Science00\(2018\) 000](https://doi.org/10.1016/j.procs.2018.08.000)

[15] Usman Ali, Abdul Rauf, Umer Iqbal, Ijaz Ali Shoukat, Abu ul Hassan “*Big Data Analytics For A Novel Electrical Load Forecasting Technique*”, *International Journal on Information Technologies & Security*, № 3 (vol. 11), 2019 34

[16] Mohammad Hasan Ansari, Vahid Tabatab Vakili and Behnam Bahrak, Ansari et al “*Evaluation of big data frameworks for analysis of smart grids*”, *J Big Data* (2019) 6:109 Springer open, <https://doi.org/10.1186/s40537-019-0270-8>

[17] Aida Mehdipour Pirbazari, Mina Farmanbar, Antorweep Chakravorty and Chunming Rong, “*Short-Term Load Forecasting Using Smart Meter Data: A Generalization Analysis*”, *Big Data Cogn. Comput.* *mdpi journal* 2020, 8, 484; doi:10.3390/pr8040484

[18] N. Phuangpornpitak and W. Prommee, “*A Study of Load Demand Forecasting Models in Electric Power System Operation and Planning*”, *GMSARN International Journal* 10 (2016) 19 - 24

[19] Xue, B., Keng, J., “*Dynamic transverse correction method of middle and long term energy forecasting based on statistic of forecasting errors*”. Proceedings of Conference on Power and Energy IPEC. 2012, 253-6.

[20] Fahad, M.U., Arbab, N. Factor, “*Affecting Short Term Load Forecasting. Journal of Clean Energy Technologies*”. 2014, 2, 305-9.

[21] Khatoon, S., Ibraheem, Sing, A.K., Priti., “*Effects of various factors on electric load forecasting: An overview*”. IEEE Power India International Conference (PIICON). 2014, 1-5.

[22] H. Hahn, S. MeyerNieberg, and S. Pickl, “*Electric load forecasting methods: Tools for decision making*,” *European Journal of Operational Research*, vol. 199, pp. 902– 907, December 2009.

[23] G. Gross and F. D. Galiana, “*Short-term load forecasting*,” Proceedings of the IEEE, vol. 75, pp. 1558–1573, December 1987

[24] E. Kyriakides and M. Polycarpou, *Short Term Electric Load Forecasting: A Tutorial*, vol. 35 of *Studies in Computational Intelligence*. Springer Berlin Heidelberg, 2007.

- [25] H. Chen, C.A. Canizares, and A. Singh. ANN-Based Short-Term Load Forecasting in Electricity Markets. Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference, 2:411–415, 2001.
- [26] S. Rahman. Formulation and Analysis of a Rule-Based Short-Term Load Forecasting Algorithm. Proceedings of the IEEE, 78:805–816, 1990. REFERENCES 285
- [27] R.F. Engle, C. Mustafa, and J. Rice. Modeling Peak Electricity Demand. Journal of Forecasting, 11:241–251, 1992.
- [28] O. Hyde and P.F. Hodnett. An Adaptable Automated Procedure for Short-Term Electricity Load Forecasting. IEEE Transactions on Power Systems, 12:84–93, 1997.
- [29] M.Y. Cho, J.C. Hwang, and C.S. Chen. Customer Short-Term Load Forecasting by using ARIMA Transfer Function Model. Proceedings of the International Conference on Energy Management and Power Delivery, 1:317–322, 1995.
- [30] J.Y. Fan and J.D. McDonald. A Real-Time Implementation of Short-Term Load Forecasting for Distribution Power Systems. IEEE Transactions on Power Systems, 9:988–994, 1994.
- [31] D.B. Fogel. An Introduction to Simulated Evolutionary Optimization. IEEE Transactions on Neural Networks, 5:3–14, 1994.
- [32] H.T. Yang and C.M. Huang. A New Short-Term Load Forecasting Approach using Self-Organizing Fuzzy ARMAX Models. IEEE Transactions on Power Systems, 13:217–225, 1998.
- [33]. Jack V. Tu.: “Advantages and Disadvantages of Using Artificial Neural Networks versus Logistic Regression for Predicting Medical Outcomes.” J Clin Epidemiol, Elsevier, vol. 49, no. 2, pp. 1225-1231 (1996).
- [34] A.D. Papalexopoulos, S. Hao, and T.M. Peng. An Implementation of a Neural Network Based Load Forecasting Model for the EMS. IEEE Transactions on Power Systems, 9:1956–1962, 1994.
- [35]. Hastie T, Tibshirani R, Friedman J.: The elements of statistical learning: data mining, inference, and prediction. 2nd ed. New York: Springer Series in Statistics (2009).
- [36]. Amit Jain, B. Satish.: Clustering based Short term Load Forecasting using Support Vector Machines. roceedings of 2009 IEEE Bucharest Power Tech, vol. 3, 212 (2009).
- [37]. Heiko Hahn, Silja Meyer-Nieberg, Stefan Pickl.: Electric load forecasting methods: Tools for decision making. European Journal of Operational Research, vol. 199, pp. 902-907 (2009).
- [38] A. K. Singh, Ibraheem, S. Khatoon and Md. Muazzam, "An Overview of Electricity Demand Forecasting Techniques," *roceedings of - National Conference on Emerging Trends in Electrical, Instrumentation & Communication Engineering*, Vol. 3, No. 3, pp. 38- 48, 2013.
- [39] E. A. Feinberg, and D. Genethliou, *Applied Mathematics for Power Systems*, State University of New York, Stony Brook, US, 2001.
- [40] *Shahida Khatoon, Ibraheem, Arunesh Kr. Singh, Priti* “Analysis and Comparison of Various Methods Available for Load Forecasting: An Overview”, International Conference on innovative Applications of Computational Intelligence on Power, Energy and Controls with their

Impact on Humanity (CIPECH14) 28 & 29 November 2014

- [41] K. M. E. Nagggar and K. A. A.-Rumaih , “*Electric load forecasting using genetic based algorithm, optimal filter estimator and least error square technique: Comparative study,*” Transaction of Engineering, Computing and Technology, Vol. 6, pp. 138-142, June 2005.
- [42] K. Karabulut, A. Alkanb and A. S. Yilmaz, “Long term energy consumption forecasting genetic programming,” *Association for Scientific Research, Mathematical And Computational Applications*, Vol. 13. No. 2, pp. 71-80, 2008.
- [43] J. H. Park, Y. M. Park, and K. Y. Lee, “*Composite modeling for adaptive short-term load forecasting,*” IEEE Transactions on Power Systems, vol.6, no.2, pp.450-457, May
- [44] M. M Najafabadi1, F. Villanustre, T. M Khoshgoftaar, N. Seliya, R. Wald1, and E. Muharemagic, “*Deep learning applications and challenges in big data analytics*”, Journal of Big Data, vol. 2, pp. 1-21, Feb. 2015.
- [45] Nature. (Sep. 2008). Big Data (Specials). [Online]. Available: <http://www.nature.com/news/specials/bigdata/index.html>
- [46] Science. (Feb. 2011). Special Online Collection: Dealing With Data. [Online]. Available: <http://www.sciencemag.org/site/special/data/>
- [47] M. Edwards, A. Rambani, Y. Zhu, M. Musavi, “*Design of hadoop based framework for analytics of large synchrophasor datasets*”, Procedia Computer Science, vol. 12, pp. 254-258, 2012.
- [48] H. Jiang, K. Wang, Y. Wang, M. Gao, and Y. Zhang, “*Energy big data: a survey*”, IEEE Access, vol. 4, pp. 3844-3861, Aug. 2016.
- [49] S. B. Taieb, R. Huser, R. J. Hyndman, and M. G. Genton, “*Forecasting uncertainty in electricity smart meter data by boosting additive quantile regression*”, IEEE Trans. smart grid, vol. 7, pp. 2448, Sep. 2016.
- [50] H. Y. Yao, “*Big data and cloud computing,*” Information Technology & Standardization, Vol5, pp.21-22, 2013.
- [51] Jie Zhan, Jinxin Huang, Lin Niu, “*Study of the key technologies of electric power big data and its application prospects in smart grid*”, 978-1-4799-7537-2/14/\$31.00 ©2014 IEEE
- [52] I. Anagnostopoulos, S. Zeadally, E. Exposito, “*Handling big data: research challenges and future directions*”, Journal of Supercomputing, vol. 72, iss. 4, pp. 1494–1516, Apr. 2016.