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A Review Of Energy Demand Forecasting Technologies

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Abstract

Objective of the paper is to quote the appropriate technologies of electrical energy demand forecasting for short and long term forecasting. In addition to pros and cons of various electrical energy forecasting technologies, short term forecasting also evolved for long term forecasting also discussed in this paper. Hybrid forecasting methods also developed and under research.

Keywords: ARIMA, ANN, Fuzzy, Hybrid method

Article outline:

1. Introduction
Globally energy need has grown significantly in the past years, energy planning ,formulating strategies and energy policy recommendation are based on energy demand forecasting .To meet the vigorously growing energy demand, energy planning and power generation through that plan is needed. For that, electrical energy demand forecasting is the basis which is universally common[1]. Under estimation of demand could lead to under capacity and over estimation could lead to over capacity, both are undesired. In order to seek an optimum and accurate demand value various methods are employed from which accurate value is taken for energy planning after error analysis.

2. Types of Forecasting
Need of electrical energy demand value differs from industry to industry, nation to nation ,region to region and time to time[2] .On the basis of duration, forecasting are classified in to short term ,mid term and long term forecasting.

2.1 Short term forecasting
Aim of the forecasting is to forecast the demand needed for a short period that is for next hour or for a day[5]. Usually this kind of forecasting is essential for an industry to make their energy plan and to get a clear idea about their energy capacity and the amount of energy to be purchased[3]. In hourly forecasting, method based on HOLT winters adaptation performs good in a hour ahead. Double seasonal holts winter method for univariate provides robust model[4].

2.2 Mid term forecasting

Aim of the forecasting is to forecast the demand needed for a medium period that is for months and for few years.

2.3 Long term forecasting

Aim of the forecasting is to forecast the demand needed for a long period that is for some years to several years. Usually this kind of forecasting is done for state or nation energy plan.

3. Regression method

It employees statistical method for forecasting. A relation between load consumption with weather, day type and customer class are established. It has many sub methods namely time series method, ARMA, ARIMA, ARIMAX, ARIMAX-EP and FARMAX[6]. ARIMA and SARIMA gives better and reliable results when compared with summing up of individual forecasts. In the case of short term forecasting employs functional data analysis and peak load forecasts are performed by using a family functional linear models which is chosen by curve classification procedure.

3.1 Time series method

This method employee's historical data of energy consumption for forecasting and it is the earlier used method for forecasting. Time series method is an assumption method which considers the factors infrastructure, auto correlation, trend and seasonal variation[7]. Time series method suits for long term forecasting[50].

3.2 Pros and cons

Quite suited for long term forecasting, requires historic data and accuracy depends on continuity of historic data[8].

3.3 Auto Regressive methods

Auto Regressive moving average method which is a stationary process, ARIMA Auto regressive integrated moving average method which is on stationary process and has only two inputs (Extrusion of ARMA).ARIMAX Auto regressive integrated moving average exogenous method which involves three inputs namely weather, time and load. ARIMAX-EP is an evolutionary programming which involves method of simulating evolution and optimization algorithm[19]. FARMAX is fuzzy ARMAX which uses exogenous inputs. This method is suitable for short term load forecasting. In wind turbine application synthetic sequence of wind speed is generate with AR model and has an ability to preserve statistical characteristics of the wind speed time series[10]. AR with high pass filter is best applicable for univariate models. In interval time series method it uses VAR (vector auto regressive)) for multivariate time series shows better results IMLP (Internal Multi layer perceptron)[11] .For multivariate time series forecasting dynamic factor models can be used in which coggers regression quantiles can also be used for conditional quantiles[49].

3.4 Pros and cons

Best suited for short term and mid term forecasting, employees simple statistical approach but it demands complex mathematical model[12].

4. Similar Day Approach

4.1 Methodology

This method makes use of historical data for days of previous 1,2,3 years data of similar day. Forecasted value is obtained by using several similar days and establishing trend co-efficient[13]. This method is suitable for short term load forecasting.

4.2 Pros and cons

Simpler method without involving complex mathematical structure ,but there may be of probability of error due change in the parameters in the current situation[48].

5. Expert System

5.1 Methodology

This system is based on rules, it involves developing a software or algorithm by incorporating rules and procedures by experts(which is obtained from their experience)[14].Rule base developed uses previous five years data, similar day types weather parameters, affecting factors and knowledge about load for forecasting.

This method is suitable for short term load forecasting.

5.2 Pros and cons

Error is low but if there is a small mistake in algorithm developed may led to unfair demand value.

6. Fuzzy logic

6.1 Methodology

Working of fuzzy logic is same as that of Boolean logic, it takes input as 0 or 1 and deduces the input. Output of the system in the form of curve fitting[15]. It does not include mathematical model for forecasting. This method is suitable for short term load forecasting. It involves fuzzyfication and defuzzyfication[16]. WEFUNN (Weighted Fuzzy Neural Network) has MAPE of 6.43%, which employs weight based on degree of importance and fuzzy distance exp (-D)[17].It provides better accuracy than EFUNN (Evolving Fuzzy Neural Network)[18].

6.2 Pros and cons

Absence of mathematical model, no need of precise input and it can be employed robust forecasting.

7. Support Vector Machines

7.1 Methodology

Origin of support vector mechanism is from statistical method. It is recent powerful technique which involves classification of regression problems and defines complex input function[19]. Performs non linear mapping (Kernel function) to high dimensional space[21]. It uses simple linear function to create linear decision boundaries. Suitable Kernel can be replacement for neural network. This method is suitable for short term load forecasting[20].

7.2 Pros and cons

Both linear and non linear functions can be performed, but requires training and testing of data.

8. Artificial Neural Network

8.1 Methodology

Artificial intelligence is employed in this system. It involves three main layers namely input layer, hidden layer and output layer. Temperature, hourly load previous load, weather data are employed as inputs[21]. Certain period is taken for training and another period is taken for testing. After forming optimal structure and weightage general algorithm is developed[22]. Non linear circuit can perform non linear curve fitting, output of ANN may be of linear or non linear mathematical function of its inputs[23]. Feed back system and choosing right architecture are essential for ANN. This method is suitable for short term load forecasting as well as long term forecasting. ANN provides better results in energy consumption profile in buildings[24]. In STLF Adaptive multi layered neural network accounts the trend component and provides better results[25]. By employing simple multi layered feed forward in ANN is able to forecast with the help of temperature data alone ,with out using historical data (Efficient approach).In univariate modeling (monthly energy demand-time series), abductive network reduces data dimensionality and fed to NN ,which improves performance in ANN .Evolving ANN in STLF uses single hidden layer which is evolved by genetic algorithm and avoids the need of large use of historical data and frequent retraining[26]. ANN employing weather data along with load has increased the accuracy. Forecasting in buildings (hourly) uses feed back ANN along with hybrid algorithm for training results in higher precision[27]. In industries STLF , NN employs MLP network (Multi Layer Perceptron) has a error reduction up to 0.0099[28].Instead of using BP (Back Propagation) network , RSBP (Rough Set BP) network usage not accounts for noise data and weak interdependency and provides better results than BP network .In regional forecasting ANN model are more accurate than regression based model[29].

8.2 Pros and cons

Accuracy up to 0.5 error is possible, it is also evolved to suit long term forecasting also. Requires training and testing with data and some times hidden layer demands for multi layer[30].

9. End Use Method

9.1 Methodology

Based on the estimation of end use energy .Appliances, customer use, age of equipment size of houses are the factors considered for forecasting[31]. This method is function of number of appliances and comparably accurate. This method is suitable for long term forecasting[32]. Stochastic model employed gives better results because they themselves captures any trend, seasonality and stochastic dependence. And combination of forecasts of homogeneous sectors provides better results[33]. Stochastic model gives idea of reliability and probability density function of load components, which is helpful in determining probability of not supplying demand[34].

9.2 Pros and cons

Not demands data other than energy used by end user accuracy is improved by building separate model for homogenous sectors[35]. Accuracy of forecasted value is affected if there is change in consumption pattern.

10. Econometric Method

10.1 Methodology

Economic theory and statistical techniques are employed. A relation between energy consumption and factors influencing consumption is established. Frame work is the aggregate econometric approach and consumption is a function of weather, economy, historical data and other variables[36]. An end use equation is developed by the integration of econometric approach and use. This method is suitable for long term forecasting. Relation between economic demand and energy demand is to be understood by energy planners for better energy policies[37]. In primary regression models key energy indicator which is statistically significant is fitted with OLS (Ordinary Least Square) estimation[38]. Cochrank –orcutt transformation algorithm are used to remove auto correlation effects which sets a good and stable model[38]. Model based on GDP, population, import and export are used in ANN had given less relative errors and RMSE'S (Root Mean Square Error) when compared with multiple regression models[39].

10.2 Pros and cons

Purely depends on economic factor and end user, possibilities of error in forecasted value if the economic growth varies largely[40].

11. Abductive Network

Hourly forecasting employing abductive network provides a simpler model a, automatically selects effective inputs and not demands frequent training. An adaptive neural wavelet model for STLF employs ARD (Automatic Relevance Determination) model to determine MLP'S size and forecasted after training[41]. Recombination of individual wavelet domain forecast forms accurate overall forecast. AIM (Abductory Induction Mechanism) in monthly electric energy forecasting provides an accuracy of 5.6% over the year and demands less number of inputs[42].

12. Generalised Long Memory

Stochastic model along with long memory is used to model the seasonal behavior of the load. Because seasonal long memory is seen in the data and it may be present in the load demand of other utilities with similar seasonal behavior[43]. And its results are better than SARIMA (Seasonal Auto Regressive Moving Average).

13. Hybrid Method

As an advancement and part of research and development hybrid forecasting methods are developed [47]. Some of hybrid methods are ANN-Time series method,ANN-Abductive method, Fuzzy logic-Adaptive network, Support vector mechanism-chaotic particle swarm optimization algorithm, Ellipsoidal –Fuzzy system, Flexible-fuzzy –Regression algorithm, socio economic-Demographic, etc. Genetic algorithm - HANFIS (Hierarchical Adaptive Network based Fuzzy Inference System) employs structure optimization, follows low dimension rule basis and uses clustering parameter to give better results[44].

14. Other Methods

Decomposition employs trend effect, rebound effect and dematerialization, which is used to know about the level of dematerialization and energy demand. Knowledge Based Expert System (KBES) peak load forecast values are found to be closer to actual load values with more accuracy and flexibility in updating the forecasting methods[45]. Logistic model which employs optimal Fibonaici search method for fitting of logistic trend curves to historical consumption data to get optimal asymptotes[46].

15. Conclusion

Thus various technologies for forecasting electrical energy demand are discussed. Though there are many methodologies are available opting right methodology for forecasting determines the accuracy of the forecasted value. Inspite of several factors are related to demand, the forecasting based on historic consumption pattern gives a reliable result. Research and development of various forecasting technologies focuses on reduction of errors and improving accuracy, error reduction up to 0.5 % is possible by using ANN[49]. Use of weather ensemble prediction improves accuracy and uncertainty assessment of electrical demand forecasting.

References

[1] Volkan S. Ediger , Sertac- Akar, ARIMA forecasting of primary energy demand by fuel in Turkey, Energy Policy, Volume 35, Issue 3, March 2007, Pages 1701-1708.

[2] P.P.Balestrassi, E.Popova, A.P.Paiva, J.W.MarangonLima, Design of experiments on neural network's training for nonlinear time series forecasting, Neurocomputing, Volume 72, Issues 4–6, January 2009, Pages 1160-1178.

[3] T S Dillon, S Sestito and S Leung, Short term load forecasting using an adaptive neural network, International Journal of Electrical Power & Energy Systems, Volume 13, Issue 4, August 1991, Pages 186-192.

[4] T.N. Goh, S.S Choi, S.B. Chen, Forecasting of Electricity Demand by End-Use Characteristics,Electric Power Systems Research, Volume 6, Issue 3, September 1983, Pages 177-183.

[5] Alberto Hemandez Neto, Flávio Augusto Sanzovo Fiorell, Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption,Energy and Buildings, Volume 40, Issue 12, 2008, Pages 2169-2176.

[6] Shaligram Pokharel, An econometric analysis of energy consumption in Nepal, Energy Policy, Volume 35, Issue 1, January 2007, Pages 350-361

[7] Nahi Kandil, Rene´ Wamkeue, Maarouf Saad, Semaan Georges, An efficient approach for short term load forecasting using artificial neural networks, International Journal of Electrical Power & Energy Systems, Volume 28, Issue 8, October 2006, Pages 525-530.

[8] R.E. Abdel-Aal , Univariate modeling and forecasting of monthly energy demand time series using abductive and neural networks, Computers & Industrial Engineering, Volume 54, Issue 4, May 2008, Pages 903-917.

[9] Kangji Li, Hongye Su, Forecasting building energy consumption with hybrid genetic algorithm-hierarchical adaptive network-based fuzzy inference system, Energy and Buildings, Volume 42, Issue 11, November 2010, Pages 2070-2076.

[10] Syed M. Islam, Saleh M. A1-Alawi, Khaled A. Ellithy, Forecasting monthly electric load and energy for a fast growing utility using an artificial neural network, Electric Power Systems Research, Volume 34, Issue 1, July 1995, Pages 1-9.

[11] Shuai Wang, Lean Yu, Ling Tang, Shouyang Wang, A novel seasonal decomposition based least squares support vector regression ensemble learning approach for hydropower consumption forecasting in China Energy, Volume 36, Issue 11, November 2011, Pages 6542-6554.

[12] Pedro A. Gonza´lez, Jesu´s M. Zamarren, Prediction of hourly energy consumption in buildings, based on a feedback artificial neural network, Energy and Buildings, Volume 37, Issue 6, June 2005, Pages 595-601.

[13] Qi Wua, Rob Law, An intelligent forecasting model based on robust wavelet v-support vector machine, Hong Kong Polytechnic University, Hung Hom,

Kowloon, Hong Kong, Expert Systems with Applications, Volume 38, Issue 5, May 2011, Pages 4851-4859.

[14] James W. Taylora, Roberto Buizza, Using weather ensemble predictions in electricity demand forecasting, International Journal of Forecasting, Volume 19, Issue 1, January–March 2003, Pages 57-70.

[15] Multi-period forecasting using different models for different horizons: an application to U.S. economic time series data, International Journal of Forecasting, Volume 19, Issue 3, July–September 2003, Pages 387-400.

[16] Aldo Goia, Caterina May, Gianluca Fusai, Functional clustering and linear regression for peak load forecasting, International Journal of Forecasting, Volume 26, Issue 4, October–December 2010, Pages 700-711.

[17] Tarık M.P. Nguyen, Q.D. Truong, D.T. Nguyen, T.D. Nguyen, V.D. Nguyen,An Alternative Approach to Reduce Massive False Positives in Mammograms Using Block Variance of Local Coefficients Features and Support Vector Machine, Procedia Computer Science, Volume 20, 2013, Pages 399-405

[18] Bai-Ling Zhang, Zhao-Yang Dong , An adaptive neural-wavelet model for short term load forecasting, Electric Power Systems Research, Volume 59, Issue 2, 28 September 2001, Pages 121-129.

[19] Wei-Chiang Hong , Chaotic particle swarm optimization algorithm in a support vector regression electric load forecasting model, Energy Conversion and Management, Volume 50, Issue 1, January 2009, Pages 105-117.

[20] M K Nassart and S Gruber, Stochastic end-user model for forecasting load statistics, Case Institute of Technology, International Journal of Electrical Power & Energy Systems, Volume 8, Issue 3, July 1986, Pages 182-191.

[21] Carolyn Fischer, Evan Herrnstadt , Richard Morgenstern, Understanding errors in EIA projections of energy demand, Resource and Energy Economics, Volume 31, Issue 3, August 2009, Pages 198-209.

[22] Samer Saab, Elie Badr, George Nasr, Univariate modeling and forecasting of energy consumption: the case of electricity in Lebanon, Energy, Volume 26, Issue 1, January 2001, Pages 1-14.

[23] James W. Taylor , Triple seasonal methods for short-term electricity demand forecasting, European Journal of Operational Research, Volume 204, Issue 1, 1 July 2010, Pages 139-152.

[24] P.A. Mastorocostas, J.B. Theocharis, S.J. Kiartzis, A.G. Bakirtzis, A hybrid fuzzy modeling method for short-term load forecasting, Mathematics and Computers in Simulation, Volume 51, Issues 3–4, January 2000, Pages 221-232.

[25] R.E. Abdel-Aal, Hourly temperature forecasting using abductive networks, Engineering Applications of Artificial Intelligence, Volume 17, Issue 5, August 2004, Pages 543-556.

[26] R. E. ABDEL-AAL,A. Z. AL-GARNP and Y. N. AL-NASSAR, Modeling and forecasting monthly electric energy consumption in eastern saudi arabia using abductive networks,Energy, Volume 22, Issue 9, September 1997, Pages 911-921.

[27] Ümmühan Bas_aran Filik *, Ömer Nezih Gerek, Mehmet Kurban, A novel modeling approach for hourly forecasting of long-term electric energy demand, Energy Conversion and Management, Volume 52, Issue 1, January 2011, Pages 199-211.

[28] M.S. Kandil, S.M. El-Debeiky, N.E. Hasanien, The implementation of long-term forecasting strategies using a knowledge-based expert system: part-II, Electric Power Systems Research, Volume 58, Issue 1, 21 May 2001, Pages 19-25.

[29] Ping-Feng Pai, Hybrid ellipsoidal fuzzy systems in forecasting regional elec0tricity loads, Energy Conversion and Management, Volume 47, Issues 15–16, September 2006, Pages 2283-2289.

[30] Saifur Rahman,Irislav Drezga, Identification of a standard for comparing short-term load forecasting techniques, Electric Power Systems Research, Volume 25, Issue 3, December 1992, Pages 149-158.

[31] Lacir Jorge Soares, Leonardo Rocha Souza, Forecasting electricity demand using generalized long memory, International Journal of Forecasting, Volume 22, Issue 1, January–March 2006, Pages 17-28.

[32] Diego J. Pedregal, Juan R. Trapero, Mid-term hourly electricity forecasting based on a multi-rate approach, Energy Conversion and Management, Volume 51, Issue 1, January 2010, Pages 105-111.

[33] A. Azadeh, S.F. Ghaderi, S. Sohrabkhani, Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors, Energy conversion and Management, Volume 49, Issue 8, August 2008, Pages 2272-2278.

[34] Noel d. Uri, Smooth Approximation and Forecasting of Load Duration Curves, Electric Power Systems Research, Volume 1, Issue 4, December 1978, Pages 255-259.

[35] Vincenzo Bianco, Oronzio Manca, Sergio Nardini DIAM, Electricity consumption forecasting in Italy using linear regression models, Energy, Volume 34, Issue 9, September 2009, Pages 1413-1421.

[36] Ramu Ramanathan**,** Robert Engle , Clive W.J. Granger, Farshid Vahid-Araghi,Short-run forecasts of electricity loads and peaks, International Journal of Forecasting, Volume 13, Issue 2, June 1997, Pages 161-174.

[37] Aldo Goia, Caterina May, Gianluca Fusai, "Functional clustering and linear regression for peak load forecasting" International Journal of Forecasting, Volume 26, Issue 4, October–December 2010, Pages 700-711.

[38] P. Poggi, M. Muselli, G. Notton, C. Cristofari, A. Louche , Forecasting and simulating wind speed in Corsica by using an autoregressive model, Energy Conversion and Management, Volume 44, Issue 20, December 2003, Pages 3177-3196.

[39] Samer Saab, Elie Badr, George Nasr, Univariate modeling and forecasting of energy consumption: The case of electricity in Lebanon, Energy, Volume 26, Issue 1, January 2001, Pages 1-14.

[40] Vincenzo Bianco, Oronzio Manca, Electricity consumption forecasting in Italy using linear regression models, Energy, Volume 34, Issue 9, September 2009, Pages 1413-1421.

[41] G.J. Tsekouras, E.N. Dialynas, N.D. Hatziargyriou, S. Kavatza, A non-linear multivariable regression model for midterm energy forecasting of power , Electric Power Systems Research, Volume 77, Issue 12, October 2007, Pages 1560-1568.

[42] Carlos Mate ICAI, Electric power demand forecasting using interval time series: A comparison between VAR and iMLP, Energy Policy, Volume 38, Issue 2, February 2010, Pages 715-725.

[43] James W. Taylor , An evaluation of methods for very short-term load forecasting using minute-by-minute British data International Journal of Forecasting, Volume 24, Issue 4, October–December 2008, Pages 645-658.

[44] Jan G. De Gooijer, Rob J. Hyndman, 25 years of time series forecasting, International Journal of Forecasting, Volume 22, Issue 3, 2006, Pages 443-473.

[45] Pei-Chann Chang, Chin-Yuan, Jyun-Jie Lin, , Monthly electricity demand forecasting based on a weighted evolving fuzzy neural network approach,International Journal of Electrical Power & Energy Systems, Volume 33, Issue 1, January 2011, Pages 17-27.