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A Survey on Electric Power Demand Forecasting

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Abstract: Recently there has been tremendous change in use of the forecasting techniques due to the increase in availability of the power generation systems and the consumption of the electricity by different utilities. In the field of power generation and consumption it is important to have the accurate forecasting model to avoid the different losses. With the current development in the era of smart grids, it integrates electric power generation, demand and the storage, which requires more accurate and precise demand and generation forecasting techniques. This paper relates the most relevant studies on electric power demand forecasting, and presents the different models. This paper proposes a novel approach using machine learning for electric power demand forecasting.

Keywords: Electric demand forecasting, short-term load forecasting, machine learning.

1. Introduction

Electric load forecasting is essential for smooth energy exchange in various electrical domains such as energy generation, energy transmission, energy distribution. The accurate load forecasting helps in the operation and scheduling of a utility company. Load forecasting based on the predicting time span, can be broadly divided into mainly four types: Very Short Term Load Forecasting (VSTLF) forecast demand minutes to hours; Short Term Load Forecast (STLF) forecast demand ranges in days, while Medium Term Load Forecast (MTLF) and Long Term Load Forecast (LTLF) forecasts are longer than a year. Load forecasting methods are categorized into three major groups: traditional forecasting techniques, soft computing techniques, lastly modified traditional techniques.

Due to emerge of new electric appliances and penetration of renewables, the electricity industry has seen ground breaking changes in the energy demand and supply over the last few years in India. This results to over or under estimation of electricity load. Over estimation results in unused power, whereas under estimation causes power deficiency, which results in power outage in rural areas. To tackle this problem, proper methodology with almost accurate solution is required.

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Existing demand forecasting methods doesn't consider local weather, economic growth, class of customer, social parameters, environmental and climate change. This is supposed to be the biggest shortcoming of traditional methods.

Hence a need of novel method is required which would incorporate climatic as well as environmental changes to get more accurate predictions. For improvement in the accuracy of the predicting model, yearly load growth with population growth can be predictable and employed as load affecting factors. The load demand may also increase because of the socio-economic factors, like massive occasion, sporting competition, religious occasions like Diwali, Christmas, Ramzan Eid, Carnivals etc. The load demand varies during weekdays and weekends. The climate decides the typical weather conditions above the defined period in particular fixed area, which also have impact on demand. The weather decides the state of the metrological features like temperature, humidity, wind, rainfall etc. which further decides the load demand.

2. Literature Survey

Rahma et al. [1] presented the combination of machine learning and big data approach for electricity generation prediction, to predict amount of power required for United States. Here authors proposed data analytic to process power management data which was collected for past 20 years. The back propagation neural network model is used for prediction. The designed framework has three stages, First, processing of raw data and future extraction, second, standardize the data in the organized format using Hadoop then third, training the back propagation ANN for the forecasting. The MAPE is calculated for both, entire generation prediction and separate state prediction. It was 4.13% on behalf of total power generation, then 4-9% for separate state prediction.

Braun et al. [2] proposed multiple regression analysis towards forecast power and gas intake of super market for UK. The authors considered consumption data and weather data for year 2012.The future energy was predicted for the next year. The multiple regression analysis established relationship between dependent variable, energy consumption and independent variables, predictors. The model was assessed by means of normalized mean biased error (NMBE) and coefficient of variation of the root mean square error (CVRMSE).

Almeshaiei et al. [3] presented electric power load forecasting for Kuwaiti electric network. The time series segmentation and decomposition along with statistical analysis was used for decision making using probability plots.

Haque et al. [4] presented performance evaluation for different optimization algorithm of daily forecast. The authors proposed hybrid model on behalf of short-term load forecasting founded on Wavelet transform, Fuzzy ARTMAP plus FireFly. The authors used wavelet transform in conjunction with Fuzzy ARTMAP, whose output was enhanced using FireFly optimization algorithm.

Che et al. [5] presented hybrid model for short term load forecasting. For this authors considered seasonal cycle, where load was changed as per the season. The multiple linear regression was used to analyze time series data through seasonal cycle. To improve effectiveness of multiple linear regression, support vector regression (SVR) with optimal training subset (OTS) was also used. The proposed model was evaluated for California electricity market data with MAPE value 3.5%.

Li et al. [6] presented IoT centered self-learning home management system aimed towards very short-term load forecasting. The authors proposed a long short-term memory recurrent neural network (LSTN RNN) model aimed at electricity price prediction. For clustering the price data k-means clustering was used.

Javed et al. [7] presented the machine learning approach with IoT to improve energy consumption of a commercial building. The system was developed using random neural network (RNN). The random neural network was trained with particle swarm optimization (PSO) also sequential quadratic programming (SQP) optimization algorithms. Training dataset was generated using Fangers equation for PMV. The result shows that energy consumption of the building was reduced by 19.8%.

Li et al. [8] presented short-term load prediction, aimed at electrical vehicle charging station. The authors proposed forecasting model based on convolutional neural network (CNN) as well as lion algorithm (LA). The effectiveness of lion algorithm was enhanced through niche immunity algorithm. Niche immunity lion algorithm (NILA) searches for optimal weights with thresholds of CNN. This system was trained using CNN model.

Daneshi et al. [9] presented long term load prediction for electricity marketplace, region New England. The authors proposed multi-layer perceptron (MLP) for forecasting, to adapt over training in the direction of complex relationships besides fuzzy logic to simulate uncertainties of real data.

Guan et al. [10] presented very short-term load forecasting for region New England. The authors proposed wavelet neural network (WNN) to perform moving forecasting for every five minutes.

Zhang et al. [11] presented index with classification approach aimed at load pattern analysis for large electricity customers in Northern China. The authors proposed k-means plus self-organizing map (SOM) for cluster load curves of customers.

Agrawal et al. [12] presented long term load prediction by recurrent neural network, which consist of long short term memory network. The authors used ISO New England Electricity dataset for years 2004 to 2015. This has total 105120 records by fields like load demand for entire region, dry bulb temperature, dew point temperature then day ahead locational marginal price. The data of years 2004 to 2009 was used for training and years 2010 and 2011 was used for testing. The RNN with LSTM network keeps both long-term and short-term states, so it was resulted in better accuracy. This model has three LSTM layers, each consists of 15 neurons. The output of each layer was given as input to the next layer. At every layer corrected linear unit was used as activation function.

Singh et al. [13] presented short-term load forecasting by ANN through different profiles aimed at weekdays also weekends. The ANN using 20 neurons were used to predicting load of NEPOOL region of ISO New England. The model was trained with hourly data for years 2004 to 2007 and was tested through the data of the year 2008. This proposed ANN prototype has three layers, which are: first input layer, second hidden layer and third output layer. The sigmoid activation function was for hidden layer and linear activation function used for the output layer.

Niu et al. [14] proposed support vector machine and ANN to short-term load prediction. The authors used data of December 2004 of Baoding Hebei Province, which consist of 720 data points. These data tuples were divided into three types of high load, medium load then low load. The ANN was used to forecast load type and SVM was used for load forecasting. The data tuples concerning 1st December 2004 to 25th

December 2004 were used to train ANN-SVM and data tuples concerning 26th December 2004 to 30th December 2004 were used for testing.

Lekshmi et al. [15] proposed time series autoregression integrated moving average (ARIMA) model for short-term load forecasting of 400 kv substation. In this work authors considers one day and one week data samples of the time interval of one minute to train and test the deployed prototype. It was detected that if the number of samples considered are increased, the error is decreased, also error is decreased if the ambient temperature is considered.

Kong et al. [16] proposed a long short term memory centered deep learning framework for short term load prediction based on resident behaviour. In this work authors used AMPds dataset, which consist of minutely current reading of a Canadian house with nineteen appliances intended for a complete year. This LSTM model was trained and tested using almanc of minutely power (AMPds) dataset. Also feed forward neural network (FFNN) with K-nearest neighbour (KNN) implemented to compare results. In this work authors addressed the volatile problem of the resident's activity.

Xie et al. [17] presented long-term retail energy prediction using regression analysis with survival analysis. The survival analysis was used to forecast customers, those will remain with the electricity company. In this work authors developed two models, first one to forecast load per customer and second one customer attrition and forecast tenured customers. To forecast load per customer, the Hong's load forecasting technique was used.

Niu et al. [18] presented hidden markov model aimed at mid long term load prediction. The periodic peak load from year 2001 to 2007 of local grid was used as dataset to train and test hidden markov model. This trained HMM was used for searching variable of interested dataset pattern. The prediction was done through interpolating the adjacent values of these dataset.

Sun et al. [19] presented support vector machine based on mass recruitment with group recruitment continuous ant colony optimization (MG-CACO) model for mid-term and long-term power demand forecasting. The SVM regression was used for finding a nonlinear map after input space just before output space with map the data for a higher dimensional feature space over the map. To select parameters of SVM ant colony algorithm was used.

Imani et al. [20] presented long term and short-term memory network in conjunction with support vector regression aimed at short term load prediction. The authors performs experiments in this work using almanc of minutely power dataset (AMPds). In this work LSTM was intended for feature extraction, whereas support vector regression model was intended for short term load prediction. The authors considers three cases; First, two separate LSTM networks were intended to load and temperature feature extraction. Then SVR was used for forecasting. Second, in addition to first case, load with temperature time series of previous 24 hrs. were specified as input to SVR for forecasting. Third, this LSTM was intended to feature extraction and load prediction.

Hamadi et al. [21] presents linear fuzzy regression model for long-term power demand prediction. The linear regression model was a linear combination of load affecting factors, such as load growth, annual population growth, economic growth, total industrial output etc. of previous year. The authors performs experiments using load data of Liaoning Province between year 1989 to 2007.

Ma et al. [22] proposed short term load forecasting using isolation forest (iForest) and long short-term memory (LSTM) recurrent neural network. Isolation forest algorithm was intended towards prepossesses the historical data. It clears the anomalies present in the dataset. The historical data was selected from city Power Company for the period 1st Jan 2016 to 7th Jan 2017. To forecast the short-term load, LSTM model was developed. It uses the sigmoid activation function in forgetting gate for control the retention of the state information in the cell.

3. Limitation of Existing System

The clustering will be more time-consuming task, when the dataset size is very large, so multi-level clustering methods should be developed [11]. The weather parameters and customer class can be taken into account, to improve forecasting results [13]. The large number of load samples are required for more accuracy, using ARIMA load forecasting model [15].

4. Proposed System

Figure 1 shows the flowchart of the proposed system. It consists of five steps as discussed below.

A. *Step I- Dataset formation:*

As per the forecasting model the dataset is prepared. e.g. if data is monthly it should be divided as day wise, hour wise.

B. *Step II- Dataset cleaning amd pre-processing:*

Data is prepared for analysis by removing inaccurate, incomplete, irrelevant, duplicated, and improperly configured data. Then dataset is divided in two parts as training dataset and testing dataset.

C. *Step III- Model learning:*

The machine learning algorithms are selected and trained using training dataset. For the better accuracy different models are combined together.

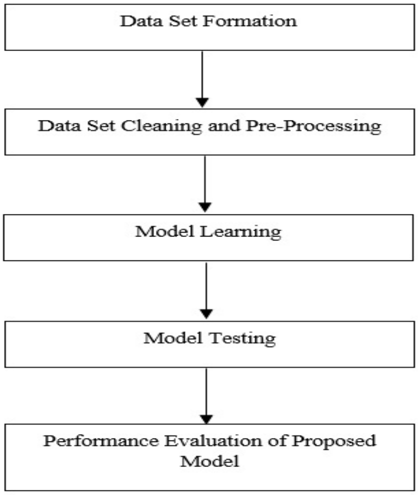

Figure 1: Flow Chart of Proposed System

D. *Step IV- Model testing:*

Once the learning is over, model is tested using testing dataset.

E. *Step V- Performance evaluation of the proposed model:*

After the testing, the proposed model assessed and evaluated for higher accuracy using different parameters like MAE, MAPE and RME parameters.

5. Conclusion

This paper relates the most relevant studies on electric power demand forecasting. It emphasizes on the different machine learning models and the data sets used in the era of electric power demand forecasting.

References

[1] M. N. Rahman, A. Esmailpour and Junhui Zhao," Machine learning with big data an efficient electricity generation forecasting system", Elsevier, Big Data Research,Vol.no.5, pp. 9-15, Sept.2016.

[2] M.R.Braun, H.Altan and S.B.M.Beck, "Using regression analysis to predict the future energy consumption of a super market in the UK", Elsevier, Applied Energy, Vol.no.130, pp. 305-313, Oct.2014.

[3] Eisa Almeshaiei and H.Soltan, " A methodology for electric power load forecasting", Science Direct, Alexandria Engineering Journal, Vol.no.50, Issue 2, pp. 137-144, June 2011.

[4] A.U.Haquea, P. Mandalb, J. Menga and R. L. Pinedab, "Performance Evaluation of Different Optimization Algorithms for Power Demand Fore-casting Applications in a Smart Grid Environment", Science Direct, Procardia Computer Science, Vol.no.12, pp. 320-325, Sept 2009.

[5] Jin Wing Che, "A novel hybrid model for bi-objective short term electric load forecasting", Elsevier, Electrical Power and Energy Systems, Vol.no.61, pp. 259-266, March 2014.

[6] Weixian Li, T. Logenthiran, V.T. Phan and W.L. Woo, "Implemented IoT based self-learning home managemt system (SHMS) for Singapore", In proc. IEEE, Internet of Things Journal, Vol.no.5, Issue 3, June 2018.

[7] A.Javed, H. Larijani and A.Wixted, "Improving energy consumption of a commercial building with IOT and machine learning", IEEE, Journals and Magazines, IT Professionals, Vol.no. 20, Issue 5, pp. 30-38, Sept. 2018.

[8] Yunyan Li, Yuansheng Huang and Meimei Zhang, "Short term load forecasting for electric vehicle charging station based on niche immunity lion algorithm and convolutional neural network", MDPI, Energies, Special Issue on Short-Term Load Forecasting by Artificial Intelligent Technologies, Vol.no.11, Issue 5, pp. 1-18, May 2018.

[9] Potharaju, S. P., & Sreedevi, M. (2018). A novel cluster of quarter feature selection based on symmetrical uncertainty. Gazi University Journal of Science, 31(2), 456-470.

[10] C.Guan, P.B.Luh, L.D.Michel, Y. Wang and P.B.Friedland, "Very short term load forecasting: Wavelet neural network with data pre filtering", IEEE Trans. Power Syst. Vol.no.28, issue no.1, 2013.

[11] T.Zhang, G.Zhang, J.Lu, X.Feng and W.Yang,"A new index and classification approach for load pattern analysis of large electricity customers", IEEE Trans. Power Syst.,Vol.no.27, Issue no.2, pp. 153-160, 2012.

[12] Rahul Kumar Agrawal, Frankle Muchahary and Madan Mohan Tripathi, "Long term load forecasting with hourly predictions based on long-short-term-memory networks", In proc. IEEE Conference Texas Power and Energy Conference (TPEC), 12 March 2018.

[13] Saurabh Singh, Shoeb Hussain and Mohammad Abid Bazaz, "Short Term Load Forecasting Using Artificial Neural Network", In proc. IEEE Conference on Image Information Processing, International, pp. 159-163, 12 March 2018.

[14] Dong-Xiao Niu, Qiang Wanq and Jin-Chao Li, "Short term load forecasting model using support vector machine based on artificial neural network", in proc. IEEE Conference on Machine Learning and Cybernetics, (ICMLC) International, pp. 4260-4265, 07 November 2005.

[15] Potharaju, S. P., Sreedevi, M., & Amiripalli, S. S. (2019). An Ensemble Feature Selection Framework of Sonar Targets Using Symmetrical Uncertainty and Multi-Layer Perceptron (SU-MLP). In Cognitive Informatics and Soft Computing (pp. 247-256). Springer, Singapore.
[16] Weicong Kong, Zhao Yang Dong, David J Hill Fengji Luo and Yan Xu, " Short term load forecasting based in resident behaviour learning", IEEE Transactions On Power Systems, Vol. 33, No . 1, pp. 1087-1088, January 2018.
[17] Jingrui Xie, Tao Hong and Joshua Stroud, "Long term retail energy forecasting with consideration of residential customer attrition", IEEE Transactions On Smart Grid, Vol. 6, No. 5, pp. 2245-2252, September 2015.
[18] Dong Xiao Niu, Bing En Kou and Yun Yun Zhang, " Mid long term forecasting using hidden markov model", In proc. IEEE International Symposium on Intelligent Information Technology Application(IITA), pp.481-483, 31 December 2009.
[19] Wei Sun and Wei Zhao, " Mid long term power load forecasting based on MG-CACO and SVM method", In proc. IEEE, International Conference on Future Computer and Communication,Vol.no.1, pp. 118-121, 28 June 2010.
[20] Maryam Imani, "Long short term memory network and support vector regression for electrical load forecasting". In proc. IEEE International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET), 28 October 2019.
[21] H.M. Al Hamadi, " Long term electric power load forecasting using fuzzy linear regression technique", in proc. IEEE Conference on Power Engineering and Automation, pp. 96-99, 19 January 2012.
[22] Yuan Ma, Qian Zhang, Jinjin Ding, Qiongjing Wang and Jinhui Ma, " Short term load forecasting based on iForest LSTM", In proc. 14th IEEE Conference on Industrial Electronics and Applications (ICIEA), pp. 2278-2282, 16 September 2019.