Comprehensive Electric load forecasting using ensemble machine learning methods

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Abstract— **The accuracy of electric load forecasting is crucial when working on applications in power grid decision-making and operation. Due to the non-linear and stochastic behaviour of customers, the electric load profile is a complicated signal. In this paper, authors propose machine learning based automated system for electricity load forecasting, taking into consideration various variable factors that have an impact on the future electricity load demand. Three machine learning algorithms are used for evaluation of the proposed framework. The algorithms are evaluated on electricity load data collected from eastern region of Ontario, integrated with the weather and population data of the region. The Light GBM algorithm comparatively performs best with mean absolute error of 0.156. The developed system can be used for more accurate and efficient load forecasting applications.**

Keywords—Time series, Machine learning, ensemble learning, Electricity load prediction

I. INTRODUCTION

The analysis of time variant real-life events and approximation of a pattern depends on the time series forecasting. In the prediction of future events based on the study of past series of events, time series forecasting is used. Due to large scope and possibilities in solving real-life problems using time series forecasting, it has become a topic of interest in various fields including medical, traffic monitoring, finance, energy consumption and various others. The accuracy while estimating the variations in time series for future and analyzing the seasonality and trend in the data is important for the accuracy of a prediction system.

Time series forecasting plays a crucial role in various temporal events including prediction of electricity load consumption. Not only is accuracy important for electric utility companies when estimating the variations in electric load for the future, but also it is considered vital to customers due to its application in the operation of the power grid and its decision making [1]. The major features which can be considered as hindrances while forecasting of electric load in upcoming days are supposed to be quite influential and they can resist the accuracy in prediction. Some of the influencing features are temperature, variable climate, humidity, occupancy pattern, social conventions and calendar indicators. The valid mapping of these influencing features and load variation is quite cumbersome because of non-linear and stochastic behaviour of electricity consumers. In the same context, the emanation of communication technologies, advanced metering infrastructure (AMI) and sensing methodology in the smart grid, has enabled researchers to monitor, analyze and record the effects of influencing features on electric load prediction [2]. After going through various research literatures, it was founded that both computational intelligence and classical (time series) methods had been already applied for forecasting the electrical load. This both utilized methodologies have their own limitations like, the classical method was criticized for having limitations of disability for handling non-linear data and beside this, the computational intelligence method was blamed for issues like limitations in learning capacity, handcrafted features, impotent learning, insufficient guiding significance and inaccurate appraisal. But at some extent, the above-mentioned issues are resolved by using few existing machine learning models for forecasting and they have achieved some improvement in the performance by using ingenious design.

The problem which is arising as an obstacle by influencing factors needs to be resolved because the negative consequences of the tiniest prediction error are leading to huge economic loss. For instance, one percent increase in prediction error will cause a 10 million increase in overall utility cost [1]. Therefore, the electrical companies are striving very hard to come up with some decent solutions in terms of developing robust, fast, accurate, and simple short-term electric load forecasting. In the previous two decades, various predictive models have been created due to utilization in the decision-making of the power grid.

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II. LITERATURE REVIEW

Boroojni et al [3], put forward a generalized method to create a model so as to get offline data which has various seasonal cycles, like daily, weekly, quarterly and annually. With the help of auto-regressive and moving average (ARMA) components, seasonal and non-seasonal lead cycles can be modeled separately.

The electric supplier needs predictions for balancing the electric load, demand management and supply to use by the electricity producing plants which has capability up to the required demand level. In the period of prediction, forecasting is categorised into the three major parts as (i) Long-period, (ii) Mid-period, (iii) short-period. All three categories are required for smooth line the electric load balancing, demand and supply, depending upon the requirement of the market. All three mentioned divisions are thoroughly investigated in the recent years, with different features, parameters and perspectives. The reviews of the research works can save the consumptions of electricity pattern from the estimation of future consumption values [mid- term electricity]. There are different machine learning models and statistical models as well, and that are used as a source of data about the electrical power consumption from the given datasets. These numbers of data repositories have time series representations which are based on uni-variant or multi-variant datasets. Time series datasets can have examinations in specific time stamps which vary in time, ranging from seconds to years. These time series datasets can be obtained where the values of data is varying with respect to time, for an example in stock market.

In the previous research author used a hybrid short term electric lead forecasting. This framework consisting of some important module like feature engineering and pre-processing of data, training module and predictive module with an optimizing module author have used MMI Technique (modified mutual information) for feature selection module and feature data pre- processing factored conditional restricted Boltzmann machine (FCRBM), deep learning model that is used for training and forecasting method for optimization. They have used Genetic Wind Driven (GWDO) algorithm [4]. They compared four different benchmark models forecasting method which are Bi- Level ANN based accurate and fast converging (AFC-ANN), mutual information based artificial verbal network (MI-ANN) and long short- Term memory (LSTM). The finalized data set for model is based on historical load data on hourly basis using. Three USA power grid which is available publicly PJM electricity market. Accuracy authors get from MI-ANN is 31.2% Bi- level = 17.3%, AFC=ANN=4.7% as a forecast accuracy, the average execution time of developed model is 52S, where every model having different. Therefore, execution like AFC ANN is 58 s, Bi-level is 1025, MI- ANN is 16.5s and LSTM is 6S for the simulation of LSTM model is MATLAB is used as simulation platform.

The work has been done by Deepika et al [5] exploring the solution for a big issue of service providers in area of cloud computing. In this paper author uses regression technique to forest the virtual machine load consumption. This approach having enough potential to produce good results using machine learning approach named multilayer perceptron model. During the analysis process the model provides the accuracy of 91%.

III. MATERIALS AND PROPOSED METHODOLOGY

The current section in this article is separated into two different sections, with first part consisting of data gathering which defines the source and size of the data and describes the dataset details. Precisely, it defines various parameters of the dataset and their types. The second part mainly concerns about the proposed methodology along with algorithms used for evaluation. The subsection provides a brief explanation about dataset pre-processing and steps which are necessary in feature selection.

A. DATASET

The complete dataset was acquired from different sources to assemble a more comprehensive data on all the variable features that influence or affect the electricity load of a place. For evaluation of the algorithm authors have used Ontario dataset of Energy Load Consumption. The data was collected from May 2003 to January 2016. The data is recorded hourly from ten different cities/regions. For the initial experimentation authors have used the data of the east region of Ontario. The data contains 7 different columns namely “Day ID”, “Date”, “Time”, “Days of week”, “Holiday”, “Id” and “Load”. Total number of observations are 111072. Table I provide details of dataset –

Table 1 DATASET DESCRIPTION

Parameters	Type	Description
Day ID	numerical	-
Date	‘yyyy-mm-dd’	2003-05-01 - 2015-12-31
Time	‘hh:mm:ss’	01:00:00 – 23:00:00
Day of Week	categorical	{0,1,2,3,4,5,6}
Holiday	categorical	{0, 1}
Load	numerical	-

Population and weather data corresponding to the location and the timestamp was collected through different legitimate sources for extensive study of the overall factors affecting the electricity load of a geographical location. The weather data collected consists of 26 parameters related to different sectors like pressure, sea level pressure, wind speed, wind direction, temperature, relative humidity, cloud coverage, solar radiation, solar elevation angle and etc. Population data was collected month wise for a particular location. These parameters were and analyzed and after proper feature selection were integrated with the electricity load data.

B. METHODOLOGY

The adequate mapping of the parameters for electricity load forecasting requires proper analysis of the parameters in the feature set. The population data was preprocessed before integrating with the electricity load data. For feature selection authors have used Pearson correlation method for computing pairwise correlation between the parameters and filtered the result with respect to load consumption. The Fig. 1 represent the correlation values –

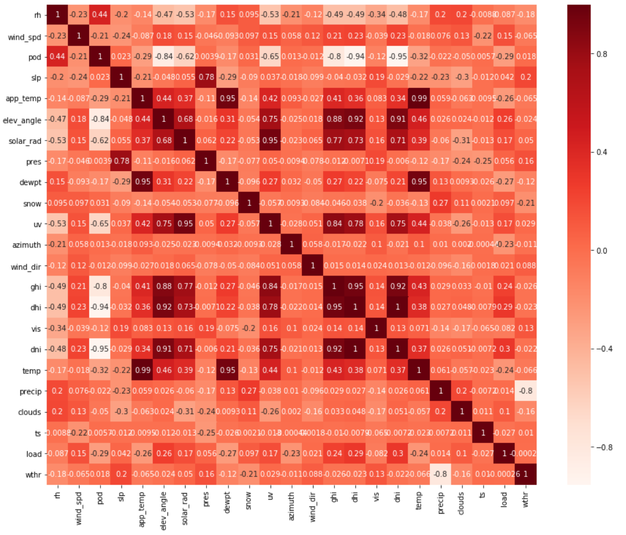

Fig. 1 Parameter Correlation

The parameters filtered out in feature selection are integrated with the main data and the population data. The final integrated dataset values are normalized by scaling the values to unit variance and removing mean value for each parameter independently and the preprocessed data is structured in stepwise format with prediction capability of 1 hour in future. The dataset is used for the evaluation of the algorithms. Three machine learning algorithms were evaluated on the dataset after splitting the dataset into training and test sample set. Time series analysis necessitates sorting algorithms capable of learning time-dependent patterns across a variety of models for other than image and sounds. Authors have used ensemble machine learning algorithms based on decision tree for the electric load data approximation. The Machine Learning algorithms used by authors for experimentation are Light GBM, Extreme Gradient Boosting and Random Forest.

Light Gradient Boosting Machine

LGBM [6] is a boosting framework based ensemble machine learning algorithm that uses decision tree as the base algorithm. The algorithm splits the tree leaf wise as opposed to other boosting algorithms that split tree level wise. The algorithm can handle large size data while maintaining low memory usage and keeping low execution time comparatively.

Extreme Gradient Boosting

It is also an ensemble machine learning algorithm based on boosting technique that uses decision tree as an estimator. Decision trees are made use of consecutively in this particular approach. In XGBoost [7], weights are vitally important. Variables, which are independent, are given weights which are subsequently put into the decision tree, which will be able to predict results. The weight factors that are predicted incorrectly by the tree have been enhanced, and these variables are put into the second decision tree to increase the quality. Next, this bunch of classifiers or predictors are then brought together to come up with a more powerful and precise model.

Random Forest

In contrast to utilizing the whole collection of features to train the models, the random forest classifier [8] uses an optimum subset of features at each split to train the models. The random subset of characteristics de-correlates the training models even further, resulting in improved overall performance. As a parameter, the number of characteristics in the subset can be specified.

IV. Experimental Results and Discussion

The scaled and preprocessed dataset is used for the evaluatio n of the algorithms. The dataset is split into training and testi ng set in the ratio of 90:10 with the training set containing 9 9963 data points and testing set containing 11108 data points . The experimental setup is given in Table 2 –

Table 2 EXPERIMENTAL SETUP

Name	**Parameters**
Operating System	Windows 10, 64 bit
Processor	Intel(R) Core(TM) 7100U CPU @ 2.40GHz 2.40 GHz
Installed RAM	12 GB
Graphics	NVIDIA, GeForce MX110
Graphics Memory	2 GB
Development Environment	Anaconda, Spyder
Programming Language	Python

The algorithms were evaluated and compared using three metrics, mean absolute error (MAE), mean squared error (MSE) and R squared statistic for regression. Mean absolute error refers to the average of total of absolute error calculated, in which absolute error is the amount of error in your measurements. It is the difference between the predicted value and the ground truth. MAE is given as –

$$\text{Mean Absolute Error(MAE)} = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i| \quad (1)$$

Where y_i is the predicted value and x_i is the actual value and n is the total number of data points. Similarly the metric MSE also computes the error or difference between the predicted value and actual value but unlike MAE, MSE calculates the average of square of the difference. The metric removes the negative signs and gives a final positive value clearly indicating the difference in the predictions and truth value. Squaring also emphasizes if there is large distance for a single data point as it deviates the mean helping in better assessing the algorithm. MSE is given by –

$$\text{Mean Squared Error(MSE)} = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \quad (2)$$

Where $y_i$is the predicted value and x_i is the actual value and n is the total number of data points. R squared statistic was used for computing a accuracy metric for the regression problem. R-squared (R2) is a statistical method that determines the proportion of variation which is described by an independent regression model variable or variables for a variable which is considered dependent. R-squared illustrates how much the change of one variable explains the variance of the second variable, while correlation clearly shows how strong the relationship is between an independent and dependent variable. R squared is given below as –

$$R\ Squared = 1 - \frac{SSE}{SST}(3)$$

Where SSE is Sum of Squared Errors and SST is Sum of Squared Total that refers to summation of squared difference of the dependant variable and its mean value. The results of the experiment for the given algorithms were computed using these metrics and are given algorithm wise in Table 3 –

Table 3 COMPARATIVE ANALYSIS OF THE THREE MODELS

Method	MAE	MSE	R Squared	Time taken
Light GBM	0.156	0.05	95.004	1.608s
XGBoost	**0.155**	**0.047**	**95.222**	**14.681s**
Random Forest	0.177	0.064	93.60	20.604s

The results show that XGBoost perform better than the other two algorithms. The performance of Light GBM and XGBoost only slightly differ as per compared analysis of all the metrics.

CONCLUSION

In this study we have used time series forecasting for the prediction of electricity load while taking into consideration all possible factors that can influence the electricity consumption of an area. Factors like weather condition and population are affecting the amount of electricity consumption from the experiment results. Authors have evaluated the experiment on three machine learning algorithms in which XGBoost performs best in terms of accuracy. But comparatively Light GBM algorithm's execution time is very low with negligible decrease in accuracy. As a conclusion Light GBM can be considered performing better in terms of overall efficiency.

The accuracy of the developed system can further be improved with further analysis and processing of the different factors that influence the predictions.

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