PREDICTION OF POWER GENERATION AND POWER CONSUMPTION IN THE REGION OF TAMIL NADU

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ABSTRACT

We consider the issue of power demand estimating in Multi-National Companies, Small and Large Scale Industries, Cottage Industries form the data collected from TANGEDO. A few methodologies utilizing machine learning models that perform one- step ahead expectations have been proposed. We implement a parallel and effective machine learning model to utilize energy demand from real deployments to check the precision of the efficient systems. Our outcomes show that machine learning methods attains forecast errors in mean and variance. Advantages and disadvantages of these methodologies are talked about and the arrangement of decision is found to rely upon the use case requirements.

Keyterms : TANGEDO, Tamil Nadu, Multi-National Companies

I. INTRODUCTION

The advent of new technologies has increased the people to adopt it, this directly or indirectly increases the electric power consumption. This leads to increase in the demand for power generation to meet the domestic as well as commercial purposes. The industries are growing rapidly, especially in a state like Tamil Nadu where there is a scope for thriving financially. So many Multi-National Companies, Small and Large Scale Industries, Cottage Industries have established their grounds and keen to expand, which needs regular power supply for the industries to thrive. Many households are moving towards automation, to complete their day to day activities quickly and efficiently, the household devices depend on electric power supply.

Over the most recent years, the concern for gas emission is been increasing, the development in the electrical power request, the dissemination of generation of domestic plants are based of renewables, and the mix of detecting meters and metering devices is used for power distribution grids and this has prompted the organization of a few smart grid around the world. As seen in [1], the smart grids are the key factors for developing the smart cities.

Concerning smart grid technology, many efforts is been given for creating appropriated control strategies that lift the productivity of electrical grids within the sight of end clients with the capabilities for power generation [2] - [4]. Besides, the policies of request response, which impact the profile of energy consumption by the prosumers that provides financial and efficiency of power consumption being, examined [5]. It helps to foresee the price incurred in using the electrical energy.

The algorithms for effective power utilization offer advantages to the control process in smart grids.For instance, in [6] and [7] estimation is used to survey what

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portion of the power generated and how much has to be privately stored for later utilization. Further, it discusses what fraction of load is injected over the smart grid.In addition, in [4] generation of power and consumption of power by prosumers' finds the level of energy needs to be injected into isolated grid for stabilizing the power consumption.

2. Proposed Method

The maximum power consumed in the state of Tamil Nadu on a normal day is 345.617 MU and still there is demand of 15343 MW. The Tamil Nadu Transmission Corporation Ltd has lots of electric power generation sources, namely Hydro, Thermal, Gas, Independent Power Plant, Captive Power Plant, Non-Conventional Energy Schemes and Co-generation and Bio mass, Wind and Solar. From the above mentioned power generation sources a total of 12900 MW on an average is generated daily. The total power generating capacity of Tamil Nadu is 17881 MW, it varies daily based on lighting peak, Minimum Peak and Morning Peak.

To fulfill the needs of energy of the in Tamil Nadu, Tamil Nadu Electricity Board (TNEB) has an aggregate installation limit of 10,214 MW that incorporates shares from the State, Central government and power producers.The state likewise has establishments with sustainable power sources, for example, wind farms has the ability to supply 4,300 MW.As a result of the increasing energy demand, the state has a power shortfall which is assessed to be approx. 15.9%. To meet the expanding energy demand, TNEB used various cutting edge ventures to be built throughout the following 5 years.

The TNEB operates with four thermal power stations, which are given below

- Ennore Thermal Power Station
- Mettur Thermal Power Station
- North Chennai Thermal Power Station
- Tuticorin Thermal Power Station

We work on data collected from TANGEDCO, to predict the total power to be generated after the five years and how many such plants need to be planned to meet the needs of domestic customers. This paper uses various machine learning methods to compute the scalability of power generations and consumptions.

2.1. Linear Regression

It is utilized for assessing the real values (cost, total number of calls, total sales happened and so forth.) using constant variable(s). Here, we set up connection between dependent and independent factors that suits the best line. Such line is called as regression, and that represents the condition Y= a *X + b. The linear regression is shown in Figure 1.

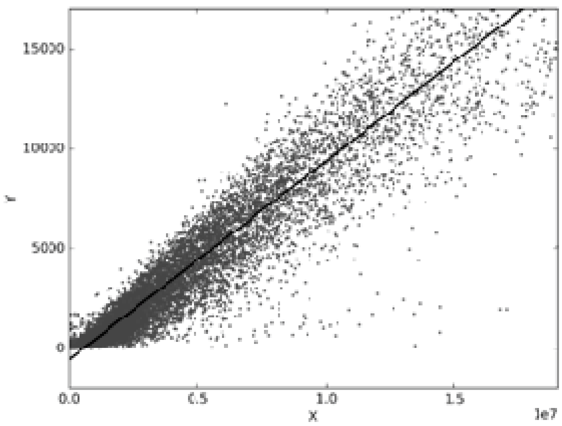

Figure 1: Linear Regression

2.2. Logistic Regression

It is utilized to find the discrete values in the light of given independent variable(s). It predicts the likelihood of event by fitting the information to a logistic work.Consequently, it is otherwise called logistic regression. Since, it predicts the likelihood that is it predicts the outcomes namely victory/lost, normal/abnormal, succeed/not succeed, its yield esteems lies in the vicinity of 0 and 1 (obviously). The graph shows the logistic regression in Figure 2.

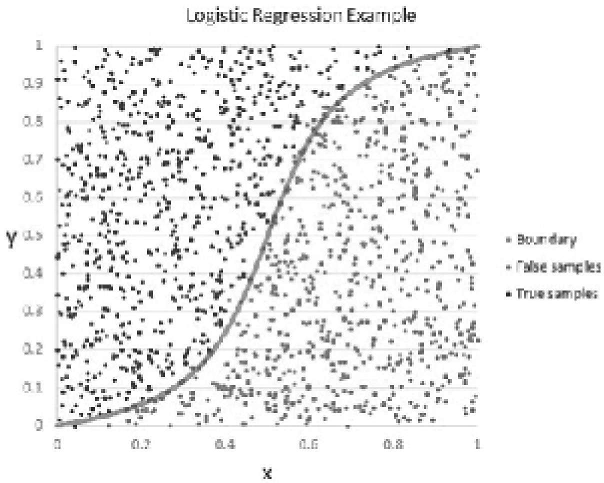

Figure 2 Logistic Regression

2.3. Decision Tree

It is a kind of regulated learning algorithm that is most utilized for reliving the issues related to classification problem. Shockingly, it works for both continuous dependent variables and categorical values. In this algorithm the population is split into two homogeneous sets. This is done in view of most significant independent variables or attributes to make as particular groups.

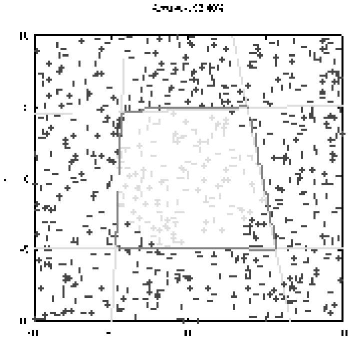

Figure 3 Decision Tree

2.4. Naive Bayes

It is a grouping strategy in view of Bayes' hypothesis with independent predictors. In straightforward terms, a Naive Bayes classifier accept that the nearness of a specific component in a class whichis irrelevant to the nearness of some other element. For instance, a natural product might be thought to be an apple in the event that it is red, round, and around 3 creeps in distance across. Regardless of whether these highlights rely upon each other or upon the presence of alternate highlights, an innocent Bayes classifier would consider these properties to autonomously add to the likelihood that this natural product is an apple. Guileless Bayesian model is anything but difficult to assemble and especially helpful for extensive informational indexes. Alongside straightforwardness, Naive Bayes is known to outflank even profoundly complex order techniques.

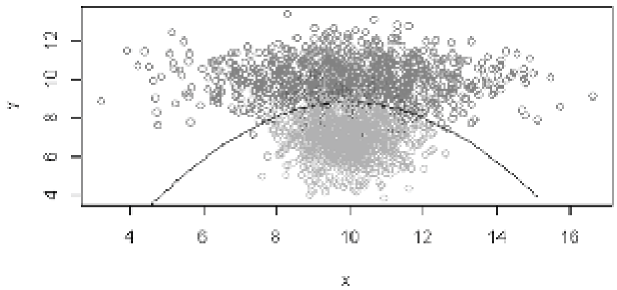

Figure 4. Naive Bayes

2.5. kNN (k- Nearest Neighbors)

It can be utilized for both order and relapse issues. In any case, it is all the more generally utilized as a part of arrangement issues in the business. The K closest neighbors is a basic calculation that stores every single accessible case and arranges new cases by a greater part vote of its k neighbors. The case being doled out to the class is most basic among its K closest neighbors estimated by a separation work. These separation capacities can be Euclidean, Manhattan, Minkowski and Hamming separation. Initial three capacities are utilized for ceaseless capacity and fourth one (Hamming) for all out factors. On the off chance that K = 1, at that point the case is essentially doled out to the class of its closest neighbor. Now and again, picking K ends up being a test while performing kNN displaying.

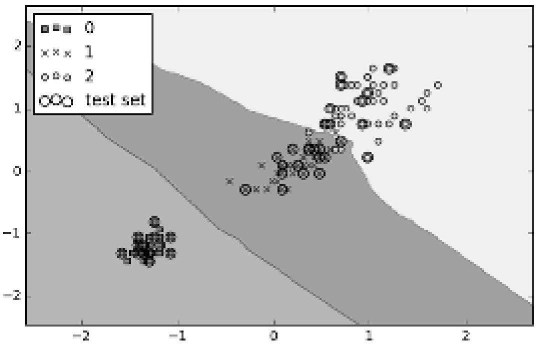

Figure 5: kNN

2.6. Random Forest

Random Forest is a trademark term for a group of choice trees. In Random Forest, we've gathering of choice trees (so known as "Woods"). To characterize another protest in the light of properties, each tree gives a characterization and we say the tree "votes" for that class. The woods picks the characterization having the most votes (over every one of the trees in the backwoods).

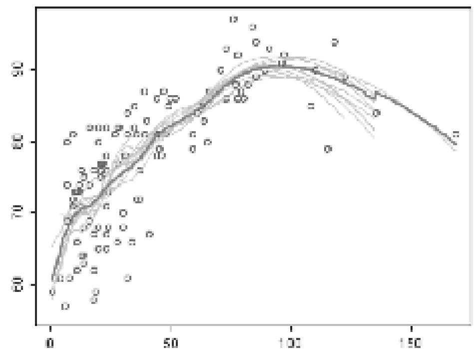
Figure 6: Random Forest

3. Results of various Machine Learning Algorithms for energy utilization

In this area, we portray the structure that to perform out the power forecast with equipment.In addition, an experimental setup is presented that includes configuration demand and power demand for numerical assessment.

So as to survey the execution of the machine learning strategies, a dataset is used that has an estimation of dynamic power utilization for an individual house. The Estimations were taken at regular intervals amid a time of 4 years, bringing about in excess of 2 million time tests. Some portion of this dataset is utilized as training set for machine learning approaches. However other time samples are utilized to evaluate the accuracy of machine learning predictions.

Table.1. Results of KNN method in Prediction of Power Generation and Consumption

Algorithm	KNN	Linear regression	Logistic regression	Naive Bayes	Decision trees	Random Forest	AdaBoost	Neural networks
Problem Type	Either	Regression	Classifi cation	Either	Either	Either	Either	Either
Results interpretable	Yes	Yes	Somewhat	Somewhat	Somewhat	A little	A little	No
Algorithm understanding	Yes	Yes	Somewhat	Somewhat	Somewhat	No	No	No

Algorithm understanding	Yes	Yes	Somewhat	Somewhat	Somewhat	No	No	No
Average predictive accuracy	Lower	Lower	Lower	Lower	Lower	Higher	Higher	Higher
Training speed	Fast	Fast	Fast	Fast (excluding feature extraction)	Fast	Slow	Slow	Slow
Prediction speed	Depends on	Fast	Fast	Fast	Fast	Moderate	Fast	Fast
Amount of parameter tuning needed (excluding feature selection)	Minimal	None (excluding regularization)	None (excluding regularization)	Some for feature extraction	Some	Some	Some	Lots
Will it Performs well with small number of observations	No	Yes	Yes	Yes	No	No	No	No
Handles lots of irrelevant features well (separates signal from noise)	No	No	No	Yes	No	Yes (unless noise ratio is very high)	Yes	Yes
Automatically learns feature interactions	No	No	No	No	Yes	Yes	Yes	Yes
Gives calibrated probabilities of class membership	Yes	N/A	Yes	No	Possibly	Possibly	Possibly	Possibly
Parametric	No	Yes	Yes	Yes	No	No	No	No
Features might need scaling	Yes	No (unless regularized)	No (unless regularized)	No	No	No	No	No

Conclusion

This paper provides a power utilization forecasting machine learning model for smart homes. Proposed machine learning models comprise of client power consumption model. The machine learning strategy depends on statistical models. Before infusing authentic information into the model, a few refinements, for example, absence of noise removing, data fixing, digitizing were connected to datasets. The Evaluation results about machine learning show how satisfactory the power consumption is.

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