Energy Consumption Forecast of GNDEC Campus

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Abstract- Energy, particularly electricity, is essential for human survival and plays a crucial role in daily life. The industry is highly tech driven with production and consumption occurring in real-time. Machine Learning and Data Science are used to address the gap between demand and supply in the electricity market. This paper examines the application of machine learning algorithms for energy consumption modeling and forecasting in smart meters. The methodology is tested on data from GNDEC Bidar, focusing on feature engineering and personalized electricity plans based on usage history.

Indexed Terms- Energy Consumption, Forecast, Machine Learning.

I. INTRODUCTION

Earth, water, air, food, shelter and energy are essential factors required for the human beings to survive on the planet. Among this, energy plays a key role for our day-to-day living, including giving lighting, cooling and heating of shelter, preparation of food and other day to day activities. Due to this interdependency, energy, specifically electricity, production and distribution became a high-tech industry. Unlike other industries the key differentiator of electricity industry is the product itself. It can be produced but cannot be stored for future; production and consumption happen almost in near real-time. This particular peculiarity of the industry is the key driver for Machine Learning and Data Science based innovations in this industry. There is always a gap between the demand and supply in electricity market across the globe. To fill the gap and improve the service efficiency through providing necessary supply to the market; commercial as well as federal electricity companies employ forecasting techniques to predict the future demand, try to meet the demand and provide curtailment guidelines to optimize the electricity consumption.

With the ever increasing and fluctuating drivers towards the energy consumption patterns it is a quite challenging task for Machine Learning researchers to build a single stop modelling solution for electricity consumption forecasting for individual users. The consumption patterns of electricity depend on the user type such as individual, office or industry. The introduction of smart meters to measure the consumption in 30 minutes granularity have provided the greatest power to Data Scientists to study the usage patterns and device the best solution for industry including forecasting, personalized electricity plans and curtailment suggestions. Typically, the consumption is depending upon socio-economic and climatic conditions of a region under consideration for the forecasting exercise. Even though the relation with these drivers and consumption looks straight forward, there are many interesting patterns available in the data which is influenced by any one or more of the above factors. To understand this better, one of the key patterns in household electricity consumption related to holidays is ‘day shoulder effect’. The day shoulder effect is the influence of a special occasion/holiday in preceding days and or following days. The obvious example is Christmas and New Year celebrations time. The household users tend to illuminate more lights during the season; even days before the actual holiday and these days consumption pattern varies on parts of the days such as evening and nights. There can be some patterns visible in the data based on the professional profile of the residents in a building. Typically, a residence with students, youngsters will be having comparatively high electricity consumption during the night; at the same time a group of working professional’s residence will be having high energy consumption during the evening and early morning. These behavioral, social and economic aspects of human life impact the consumption, hence capturing these features directly or indirectly helps the Data Scientist to build an effective model for both consumption and load forecasting scenarios in electricity industry. The current exercise focuses on investigating the use of regression techniques combined with effective feature engineering techniques to forecast the individual user's energy consumption.

II. BACKGROUND

Load Forecasting techniques are one of the widely studied aspects using various time series techniques and regression algorithms including ARM and Neural Networks. Most of the studies in this direction use statistical techniques or Artificial Intelligence (AI) algorithms such as regression, neural networks, fuzzy logic and expert systems. Apart from this there are some native techniques such as similar day approach i.e. copying the same day from previous year. Most of the statistical approaches leverage a mathematical model, which can represent a load as function. The most widely used such methods are additive and multiplicative models. Chen, Canizares and Singh [1] presented an additive model in their paper. A rule based short term forecasting technique was proposed by Rahman [2]. An ARIMA Transfer Function based approach is discussed in the paper by Cho et al [3]. Neural Network and its derivatives are being widely studied in electric load forecasting. A short-term forecasting method is presented efficient feature selection and engineering is key for any forecasting or modelling exercise. Most of the papers discussed in the previous section use different features for the modelling exercise. The raw data for energy forecasting has information such as date, time and load/consumption. In addition to this, weather data, calendar information etc. are used along with the raw data to make the prediction much reliable. More than the directly available features, lots of engineered features are included in the exercise, which shall be discussed in detail in forthcoming sections.

Feature selection in time-series data is one of the emerging and challenging area in Machine Learning. In the Big Data and IoT revolution era real-time time-series data is captured and various statistical analysis and forecasting are applied. Feature selection with reference to electric load forecasting is discussed by Mashud et al in the paper [16]. The paper discussed measures such as Prediction Interval Quality, LUBE and improved LUBE (LUBEX), Mutual Information and Correlation Based Feature Selection. A generic filter and wrapper-based approach for neural network-based time-series forecasting is studied by Sven F et al [17]. Automatic feature generation using Grammar Based techniques are discussed in the seminal book by De Silva et al [18]. Half hourly electricity consumption data from the DECC headquarters building at 3-8 Whitehall Place UK for the primary experiment. The data is available at European data initiate web portal [19]. Apart from this an experiment with Smart Meter data from EMA Singapore was conducted to understand the electricity usage patterns. Results from the same is not discussed in the paper in detail as the data is not open for public sharing. As a follow-up study to this experiment, a set of supplementary exercises with application of deep learning methodologies in load/consumption forecasting with the UK Government open data [20]. The supplementary data used for incorporating additional features in the experiment included a generic holiday list gathered from various internet resources.

III. MODELLING OF ENERGY CONSUMPTION

Before starting the formal exercise, some minor experiments with Auto Regressive Integrated Moving Average (ARIMA) and Exponential Moving Average (EMA) were conducted. These techniques were not able to accommodate the categorical features included in the data such as month etc. Considering the categorical feature in the data-set an ensemble method Boosted Decision Tree Regression (BDTR). The selected implementation is AzureML based one which leverages the Lambda MART [21].

One of the key aspects of producing the best predictive model is selecting right value for the tuning parameters for the learning algorithms. Since there are no thumb rules in pre-determining the best parameter, it is advised to do a hyper parameter optimization by manual methods or the algorithmic way. In case of manual methods, *n* models with *m* parameter sets has to be developed, and keep track of the accuracy figures and then take a decision on which model has to be selected. At the same time there are algorithms and implementations available to handle this. A selected set of hyper parameters (either a small or large/exhaustive) can be supplied to an algorithm to fit *n* models with the *m* parameter combinations. Finally, the best set of parameters which yield the maximum performance is identified and entire training data is fitted/trained with the same parameters. The algorithm for Hyper Parameter Optimization is:

1. Define sets of model parameter values to evaluate
2. For each parameter set do for each resampling iteration do

1. Hold-out specific samples
2. [Optional] Pre-process the data
3. Fit the model on the reminder
4. Predict the hold-out samples

End

Calculate the average performance across hold-out predictions

3. End
4. Determine the optional parameter set
5. Fit the final model to all the training data using optional parameter set

The common methods for Hyper Parameter optimization are: Bayesian Optimization, Grid Search, Random Search and Gradient Boosting. A detailed discussion on the topic is available on paper by Bergstra et al [24][25]. In the current exercise the authors have used the Random Search technique to get the best model. Root Mean Square Error (RMSE) and R^2 are selected as error metric. R^2 is calculated as the square of correlation between the observed y values and the predicted $\hat{y}$ values. Otherwise it can be referred as the proportion of variation in the forecast variable that is accounted for by the regression model. If the predictions are close to the actual values, R^2 *should* to be close to 1. On the other hand, if the predictions are unrelated to the actual values, then R^2= 0. In all cases, R^2 lies between 0 and 1. The use of RMSE is very common error metric for numerical predictions. Compared to the similar Mean Absolute Error, RMSE amplifies and severely punishes large errors. For model selection RMSE was considered in the Random Grid Search and for test set evaluation R^2 was used.

$$R^2 = \frac{\sum(\hat{yi} - \bar{y})^2}{\sum(yi - \bar{y})^2}$$

$$RMSE = \sqrt{\frac{1}{n}(y_i - \hat{y}_i)^2}$$

The final data set used for modelling exercise consisted of following attributes: day hour index, is the day holiday, name of the day (such as Monday), whether the day is weekend or not, maximum consumption of the day, minimum consumption of the day, demand in hour minus one and demand in hour minus two. Three iterations of the training with Regression methods has performed and evaluated the model with test data using the RMSE score. The first iteration was done using five parameters combination to the BDTR

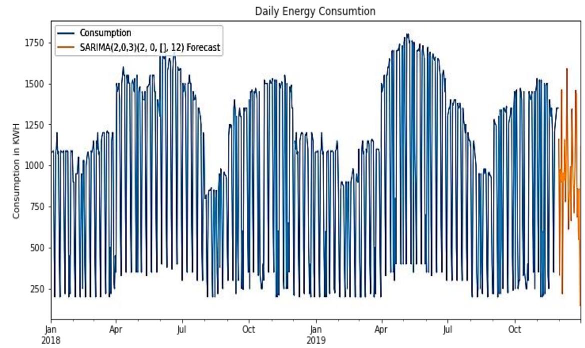

Fig 1. Daily Load Curve

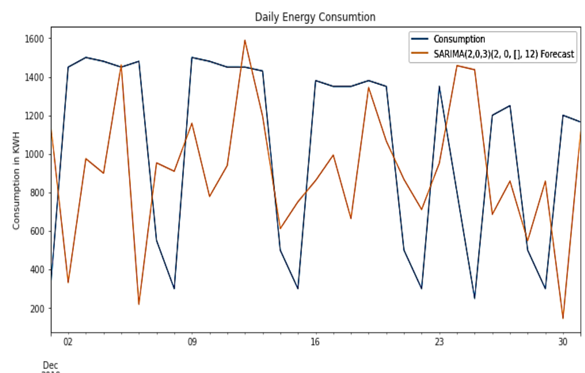

Fig.2 Daily energy consumption using SARIMA Model

CONCLUSION

From the study presented in this paper, the following conclusions can be drawn about forecasting electrical load. For the creation of accurate models, additional metrological data and demographic data must be available. The system's performance is influenced by how categorical variables are analyzed and handled, as well as by how well the chosen method and implementation handle categorical data. Granular parameter combinations and hyperparameter adjustment with a random and exhaustive grid option can result in reliable models. This will also be based on calculations for feature engineering, extraction, and relevance. Although tree-based ensemble models calculate feature significance internally, it is recommended to do a feature importance calculation with a baseline model and develop models using a variety of feature importance techniques will be having a more accurate result.

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