Non Linear Technique for Predicting Energy Consumption

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***Abstract* -- Electricity load forecasting is an active research direction in the Common Era. Electricity is one of the essential factors required for the people to survive in the modern world. The electricity market across the globe always identifies the gap between the energy demand and supply. To improve the service efficiency there is a need of management tool for the optimized utilization of power consumption for the future generation. Therefore forecasting techniques are used to predict the future energy demand and for the efficient energy management. The objective of this paper is to develop an efficient forecasting model for predicting the energy consumption. In this paper two well-known prediction algorithms namely Simple Linear Regression (SLR), Deep Learning (DL) are proposed for forecasting of energy consumption. To evaluate the performance, experiments were carried out on smart meter benchmark dataset. The experimental results shows that Deep Learning (DL) performs well on predictions with more accuracy in terms of RMSE performance metric than Simple Linear Regression (SLR).**

Keywords—load forecasting, Energy, prediction, SLR, Deep Learning

I.INTRODUCTION

Electrical energy is an integral part of human life but it is a scarce resource available to human beings. There is no possibility to live without thinking of electricity in the world. The electrical energy is one of the demanding factor in growing world. Electricity is being part of almost every fields, for example Industries, Software, Agriculture, Medical fields, Education, Government and homes etc. According to the report submitted by US-Energy Information Administration (EIA), by 2040, there will be a 28% increase in global energy demand.

Electricity generating companies are getting pressure to produce more energy by the Industries. Efforts are made in many directions to cope up with increasing worldwide energy demand. One of the way is to utilize existing energy resources in an effective manner, we can avoid unnecessary usage of energy which tends to energy wastage, and by manipulating the existing and renewable energy resources, and the power production companies should increase the capacity of production [10].

A.Types of forecasting

According to different scale and certain horizons load forecasting can be performed [12].

(i) Short Term Load Forecasting (STLF) - Forecasting of the power consumption for an hourly manner or up to a day [7].

(ii) Medium Term Load Forecasting (MTLF) - Ranges from day to a week.

(iii) Long Term Load Forecasting (LTLF) - forecasting for a month to years.

This proposed model is approaching a challenging task of forecasting [15] the power consumption at an individual household level according to the occupancy information, due to its ahead system volatility with the measurements composed of several individual components.

The power consumption of a house definitely gets vary by a number of influences, such as geographical patterns and its random effects, time of the day, different weather reporting, multiple economic factors, impact created by holidays, day of the week, operational characteristics of the individual devices and other suspicious effects. This features certainly takes the predictions results to higher error in the range of 20% to 100% according to the dwelling lifestyle with the numerous kinds of appliances.

II. RELATED WORK

A. Review on Forecasting methodologies and approaches

Yang Wang et.al [1] presented "Recent trends in Load Forecasting Technology for the operation optimization of Distributed Energy System". In that concept he stated that Load forecasting is used to predict the load data at a specific moment in future. And also discussed about the Load forecasting technologies such as Short term load forecasting (for few hours to few days in advance), Medium term forecasting (for few weeks to month in future), Long term forecasting (for one to ten years).

Qixin Chen et.al [2] presented "Review of Smart meter data analytics: Applications Methodologies and Challenges". He mentioned the three stages of smart meter data analytics followed by Descriptive, Predictive, and Prescriptive with the applications of Load analysis, Load forecasting and Load management. In load analysis how to perform outlier detection and create load profile. In Load forecasting, how to perform load forecasting with the profile. Final conclusion has been made on performing Load forecasting with smart meter data [8] analytics and how to manage the load with the created profile.

Tomasz Zabkowski et.al [3] presented "Electricity forecasting on the Individual household level enhanced based on activity patterns". They discussed about the Electricity forecasting method on Individual level based on the input collected from smart meter and individual patterns of energy consumption. These patterns are used to feed the forecasting model. He utilized the hierarchical clustering to discover the similar profiles (appliances with similar switch on). The activity patterns are identified using sequence mining method.

Baosen Zhang et.al [4] presented "A Sparse Linear model and significance test for Individual consumption Prediction". In this work, they intentionally created a sparse auto aggressive model to predict the electricity consumption of individual customers using the historical data of that users. Various Load forecasting techniques on Machine learning had experienced to improve the accuracy measure of the prediction to provide efficient energy management. Finally the performance has been established with the evaluation metrics.

Jean-Baptiste Fiot et.al [5] presented "Electricity demand forecasting by Multi-Task Learning". In this concept he discussed the method of Multi-Task learning which is focusing on predicting the demand of electricity measured on multiple power lines of an electrical network. Important factor to be considered on comparing with other forecasting methodologies it implies on new way of learning the data at the mid of the electrical network with the poor performance.

Daniel L. Marino et.al [6] presented "Building Energy Load Forecasting using Deep Neural Networks". In this work the author used the Machine Learning technology of Deep Neural Networks (DNN) prove to be more advantageous than MLP networks since they can succinctly represent a significantly larger set of functions. Some DNN achieve greater accuracy than other traditional methods. DNN still suffers from long computational times but we showed that even by having a small number of epochs, DNN architectures are still preferable.

From the literature survey presented above, the energy consumption prediction has been achieved in an aggregated manner only (By considering total electricity consumption measurements of the buildings and particular residential areas) [11]. Forecasting the electricity demand of particular appliances has been performed rarely and the algorithms used are have some backtracks on its way [16]. So this paper proposes two well-known prediction algorithms for predicting the energy consumption of particular home appliances with the comparison of results by means of accuracy for concluding the best results.

III. PROPOSED METHOD

Electricity is one of the main resource utilities for the people. To make the people understanding their demand on electrical energy and how to balance the energy consumption at household level, there is a requirement of forecasting method [13]. This paper has been proposed to build a robust forecasting model to predict the electricity load on various household devices. To develop the prediction model we utilize the smart meter benchmark dataset including the measurements of door counter sensor [9] as ground truth, for training the model as input. The Smart meter data which contributes electricity consumption measurements from various household appliances has been mentioned as features in watts [14]. In this forecasting model two well-known prediction algorithms namely Simple Linear Regression (SLR) [19], Deep Learning (DL) are proposed for forecasting of energy consumption. The intention of this paper is to create a prediction model for predicting the electricity demand at household level by applying these two prediction algorithms on a smart meter dataset. To conclude the model, the comparison has been made between two algorithms by evaluating the performance by means of Root Mean Squared Error metric to make it more efficient.

<u>Algorithms:</u>

A. Simple Linear Regression (SLR):

Input: Dataset D1 (Smart meter benchmark dataset),

Output: prediction model with performance evaluation metrics.

Step 1: Input dataset (benchmark smart meter dataset)

Variables assigned (in dataset) E.g.

X1 = Occupancy data,

Y = (Y1, Y2, Y3, Y4…)

Y1 -> Refrigerator,

Y2 -> TV, and

Y3 -> washing machine

Y4 -> Central power lights etc….

Step 2: SLR model creation

E.g. model <- lm (y1~x1) (beta co-efficient)

Step 3: statistical summarization summary ()

Step 4: Model interpretation

Call => function call to calculate the regression model

Residuals => used to provide a quick view of the distribution of the residuals,
Coefficients => beta coefficients

Residual standard error (RSE)

R-squared (R2)

B. Deep Learning (DL)

Input: Dataset D1, (Smart meter dataset)

Output: Forecasting model results with performance metrics evaluation.

Step 1: Library package installation. (library h2o)

Step 2: Feed dataset.

h2o.importFile ("D:/dataset1/sample.csv")

Step 3: Data partitioning

splits <- h2o.splitFrame(train.hex, 0.75, seed=1234)

Step 4: Deep learning model creation h2o.deeplearning(x, y, training frame, hidden, epochs).

Parameters used:

Training frame: (Required) dataset used to build the model,

Y: dependent variable,

X: predictor variables,

hidden: hidden layer sizes (e.g., 100,100),

epochs: number of iterations.

Step 5: grid model creation

h2o.grid (algorithm, grid id... hyper params = list ())

Step 6: prediction model on a test set.

IV. EXPERIMENTS AND RESULTS

The Experiments were carried out on given smart meter benchmarking dataset. The experimental results shows that the prediction results with the comparison of Simple Linear Regression with the Deep Learning [17] metric to evaluate the performance.

A. RMSE (Root Mean Squared Error)

The Root Mean Squared Error is the default evaluation metric for many models because of its smoothly differentiable loss function which makes mathematical calculations much easier. The mathematical formula to measure the RMSE value has given as follows,

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

The RMSE value indicates the simple standard deviation. It is used to measure the variances between the observed values (input values) and the forecasted values (output). The input values are also called as residuals.

B. R Squared (R^2) and Adjusted R Squared

The R squared and Adjusted R squared, both are considered as explanatory metrics of the model, because it provides the explanation for the variability in the dependent variable (i.e.) outputs based on the selected independent variable (i.e.) inputs.

R-squared also known as co-efficient of determination is a statistical performance metric to measure how close the data are to the fitted on the regression line.

It can be calculated by the percentage of variation in the response variable which is explained by a linear model. Or:

R-squared = Explained variation / Total variation

R2 can be calculated by the following equation:

R2 = 1 – S2e / S2y

Where, S2e -> sample variance of the residuals

S2y -> sample variance of outputs.

Adjusted R^2

Adjusted R squared is similar to R squared error, it measures how well the model terms fits the regression line. And the mathematical formula is,

$$R^2_{adj} = 1 - \left[\frac{(1-R^2)(n-1)}{n-k-1}\right]$$

The Adjusted R squared values always be equal or less than R squared error metric. The advantage of choosing R squared over Adjusted R squared is the marginal improvement added by the additional term.

The following table 4.1 shows the experimental results shows that Deep Learning (DL) [18] performs well on predictions with more accuracy in terms of RMSE performance metric than Simple Linear Regression (SLR) [19].

Table 4.1 Comparison of SLR with DL – Smart meter dataset

Smart meter dataset (Targets)	Simple Linear Regression (SLR)	Deep Learning (DL)
	RMSE	RMSE
Response to Y1	54.67	0.88469
Response to Y2	30.34	0.44186
Response to Y3	204.8	0.36419
Response to Y4	29.68	0.86608

The feature assignments are represented in the algorithm for the respective label descriptions in the benchmark smart meter dataset.

To effectively show the accuracy measure in terms of Root Mean Squared Error metric the above comparison table has illustrated by using the following chart.

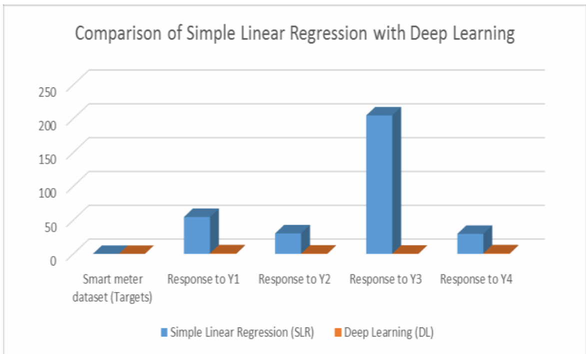

Fig 4.1 Comparison chart of Linear Regression with Deep Learning

The above figure shows that the relationship between the SLR and DL in terms of accuracy. The comparison of RMSE metric between two algorithms has explored that the DL shows more accuracy than Simple Linear Regression.

V. CONCLUSION

The optimized power utilization is the basic requirement of the current world to compensate with the demanding factors of electricity for balancing the production. There are enormous amount of existing methodologies and approaches are present for power consumption prediction. Hence it poses a significant challenge on theprocess of predicting the energy demand for different kind of household devices due to its variation. The objective of this paper is to build an efficient forecasting model to predict the demand of household energy consumption for the particular home appliances with the occupants' information. This paper utilizes two well-known prediction algorithms to create a prediction model. To make it more efficient experiments were carried out by applying the two algorithms mentioned above on a smart meter benchmarking dataset. For making conclusion the prediction results of two algorithms are compared by means of Root Mean Squared Error (RMSE) metric. The experimental results shows that Deep Learning (DL) performs well on predictions with more accuracy in terms of RMSE performance metric than Simple Linear Regression (SLR).

VI. FUTURE WORK

Security is the one of the determinant stopping metric in the recent fields. Security features are the very important considerations to ensure the complete accomplishment of the task without any security concerns. For making accurate predictions on the given data it is must to make sure that the data loaded for the process. The future work is focusing on

- Loading secured data on cloud for forecasting process to ensure the prevention of data from the security threats such as data leakage, hacking, and other privacy issues by implementing an efficient security algorithm.

- To build an ensemble model with improved prediction results having more accuracy than any other constituent model alone.

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