PROBABILISTIC SHORT-TERM MULTIVARIATE ELECTRICAL POWER LOAD FORECASTING UTILIZING NGBOOST

Arjeus Guevarra[1*], Elton Mark Lanuza[2], and Prospero Naval[3]
Computer Vision and Machine Intelligence Group
Department of Computer Science
University of the Philippines Diliman
Philippines
[a]aaguevarra2@up.edu.ph, [b]eplanuza@up.edu.ph [c]pcnaval@up.edu.ph

ABSTRACT

Electric Power load forecasting is an indispensable part of the planning and operation of a microgrid. It helps the utility in making important decisions such as generating electric power and infrastructure development. Accurate models should be determined in electric power load forecasting. In this paper, the authors experimented and evaluated NGBoost, an algorithm used in probabilistic prediction, and tested it with baseline method Vector Autoregression (VAR). For the results, NGBoost outperforms VARMAX where NGBoost yielded its lowest MSE value of 3.0267 for 15-minute time step vs MSE value of 4.1162 for VARMAX. And in terms of prediction stability, both methods produced very close values. It is therefore concluded that NGBoost proved to be useful in probabilistic predicting multivariate outcomes of electrical load.

Keywords: NGBoost, VARMAX, Probabilistic Load Forecasting, Microgrid, Machine Learning.

METHODOLOGY

The dataset used in this paper is came from the open-source multi-year power generation, consumption, and storage data in University of California, San Diego (UCSD) microgrid[6]. The machine learning pipeline is shown in **Figure 1**

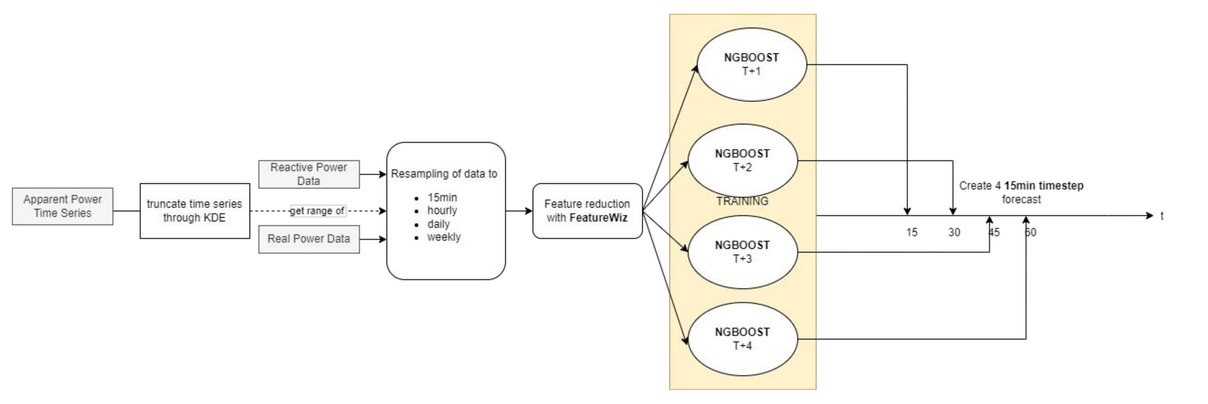

Figure 1 Pipeline and Model Architecture

For simplification purposes, only a pair of incoming power components are considered(*active* and *reactive* power). Next step is that we need to "split" the selected time period(e.g. a year) with similar characteristics as we aim to train the model with a degree of periodicity and to lessen overfitting.

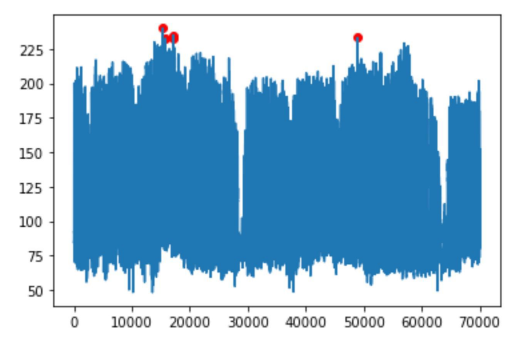

Figure 2 Pipeline and Model Architecture

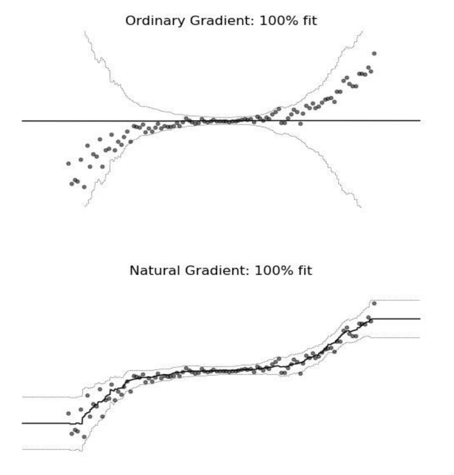

Figure 3 Ordinary Gradient vs Natural Gradient in 100% fit.
Source: https://stanfordmlgroup.github.io/projects/ngboost/

To do this *1-dimensional* clustering is performed. Kernel density estimation is used to achieve this. Quantile criteria is tuned so that 5 groups can be yielded. See Figure **2**. The last cluster(latest in timeline) is used for further training. Next is resampling the dataset to give three more time steps: Hourly, Weekly, and 12-weekly (3 months) thus, giving 4 time steps along with the original 15-minute time steps. Shiftings were performed to produced features based on their respective time steps, and concatenated to be used as the main dataset at the same time, processed by feature reduction. This uses a framework called *FeatureWiz* in selecting the most important features. *FeatureWiz* implements two techniques in finding out this best features. SULOV and Recursive XGBoost. *SULOV or Searching for Uncorrelated List of Variables* is a method which finds out variable pairs which are crossing a correlation threshold externally passed which are highly correlated. This will be used in training the NGBoost. See Figure **3.** NGBoost[4,5] instead considers parameters for probability distribution instead for expected values between predicted variables and observed features.

Prior to training using NGBoost, data shifting is done to allow NGBoost training for time series dataset. Four models was produced during the training, 1 model that uses 15-minute time step (t=1), model after 30min (t=2), up to (t=4).

As baseline comparison, the results will be evaluated using VARMAX (Vector Auto Regression Moving Average with Exogenous Regressors)[7], meaning using a multivariable Autoregressive method. Basically a walk-forward algorithm is compared against the algorithm trained with NGBoost.

Evaluation Metrics
2 methods are used for evaluation: **Mean Square Error** and **Prediction Region**:

$$MSE = \frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}$$

Prediction Region is a type of confidence interval where it provides a range of values that is likely to contain a future occurrence of an event in a multivariable setting. It is expressed in the formula

$$(Y-\mu)\Sigma^{-1}(Y-\mu)^T \le \chi^2_{p,\alpha}$$

Essentially, we intended to have $\alpha\%$ =0.25, of the chi squared distribution χ^2 . Because the authors noticed that in testing the prediction region of NGBoost as the α% increases, its quantile function increases giving it a higher chance of satisfying the inequality unlike evaluating VARMAX which behaves opposite (1-α%).

CONCLUSIONS

To conclude, NGBoost can be used as a probabilistic short-term load forecasting for Real and Reactive Power of a building. NGBoost outperforms VARMAX where NGBoost yielded its lowest MSE value of 3.0267 for 15-minute time step vs MSE value of 4.1162 for VARMAX. But in terms of prediction stability, both methods produced very close values. It is to be noted that a hyper parameter tuning was applied to VARMAX while NGBoost is not. In the future works, authors will perform hyper parameter tuning for NGBoost to check if it produces better results. Additionally, the authors will test if ensembling models of NGBoost would help in producing less mean square errors and better uncertainty prediction. Lastly, other factors such as weather, buildings, and power generation in the microgrid will be considered whether they have a relationship in terms of their producing real and reactive power for each buildings.

INTRODUCTION

Electrical infrastructure is one of the most important, and the vital part for the economic growth of the country. And electricity became part of the livelihood of the people and the industry. With this, a global demand of electricity for the industries, institutions, and residential have been booming over the past years. Therefore, different research regarding electric power load forecasting has been commenced in order for electricity generators, distributors, and suppliers in planning ahead the energies must be properly distributed to the commercial establishments and residences. As well as promoting energy conservation among the consumers. There are different types of load forecasting, short-term load forecast (STLF), medium-term load forecast (MTLF), and long-term load forecast (LTLF). These load forecasting techniques must provide predictions as accurate as possible which currently challenges the researchers in seeking the most accurate and the most efficient method. In this paper, the authors experimented and evaluated NGBoost[1], an algorithm used in probabilistic prediction where KDE is used in selecting data points from the original time series, and tested it with baseline method Vector Autoregression (VAR).Probabilistic forecasting had been significant in every time uncertainty cannot be simplified most especially if it involves complex systems. This method is an excellent technique in uncertain demand environments for instance, electrical load forecasting. Electrical load forecasting demonstrate high variability in reference to historical electricity consumption thus, needing a probabilistic method which allows for a clearer and more informative way of predicting the electricity demand.

In the study of Muzumdar [1], they experimented different machine-learning algorithms for short-term load forecasting in Consumer-Centric Microgrid Environment. By weighted average given the predicted load from these algorithms, it achieved the lowest forecasting average root-mean-square deviation and average mean absolute error of 2.41 and 1.49 respectively among other models such as ARIMA, and CNN making it the most robust. However, they did not mention testing their model in a multivariable input at the same time, producing probabilistic results. These authors also implemented probabilistic forecasting where it is based from a deterministic forecasting model. Although they did not mention that their method was also implemented in a multivariate input. Performances of different forecasting strategies for electricity consumption in buildings was evaluated in this paper [2]. The authors investigated three strategies: univariate, multivariate, and multistep with the use of XGBoost, LSTM, and SARIMA for which algorithms are performing the best in electricity consumption forecasting. XGBoost outperforms all the algorithms for univariate and multistep forecasting while LSTM showed the worst. In the paper of Segarra et. al. [3], they implemented probabilistic load forecasting for building energy models by using a building energy model (BEM) called white-box model. Their experiment got a confidence level higher than 80%. Lastly, in the paper of Yousaf, they utilized Machine-Learning-Based Feature Selection approach along with an integration strategy in Residential Electricity Load Forecasting. In their study, they used seven different autoregression models and validated through a feedforward adaptive-network-based fuzzy inference system (ANFIS) model. And best feature selection was also utilized through the use of binary genetic algorithm. In summary, all of the studies mentioned implemented energy and power load forecasting for residential, buildings, and microgrid. Some of them implemented probabilistic approach, and some of the implemented their methods in a multivariable dataset. But a few studies only experimented a method in a multivariate dataset at the same time, producing probabilistic results. In this paper, authors attempt to implement a method that is used in one of the microgrid datasets with multivariable outcomes. As well as producing a probabilistic result.

RESULTS & DISCUSSIONS

In experimenting NGBoost, four models were produced and evaluated during the training. But initially, these two datasets were evaluated and compared to check whether the feature reduction reduces the training loss or not.

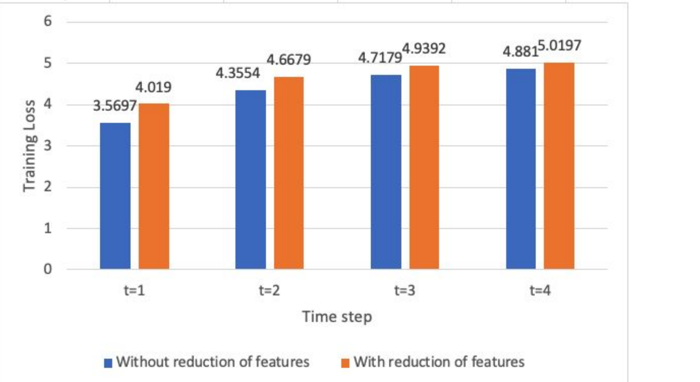

Figure 4 Training loss of 2 datasets throughout time steps

As observed in figure 4, training the NGBoost without featurewiz applied produced less training error than the dataset with reduced feature. The dataset without feature reduction was used to further evaluate the NGBoost. Vector Autoregression is also evaluated and used as a baseline algorithm to be compared by NGBoost. In this part, The dataset with applied KDE was tested if it is stationary by using Dickey-Fuller Test. As it turns out, the dataset is indeed stationary. For hyper-parameter tuning, best values for p and q is determined by using grid search. Inference for NGBoost and VARMAX is evaluated on 4 different time offsets given their respective test sets using Mean Square Error (MSE). For instance, 1 model trained in 15-minute time offset is tested given test set with 15-minute time offset, 1 model trained in 30 minute offset time step. and so on.

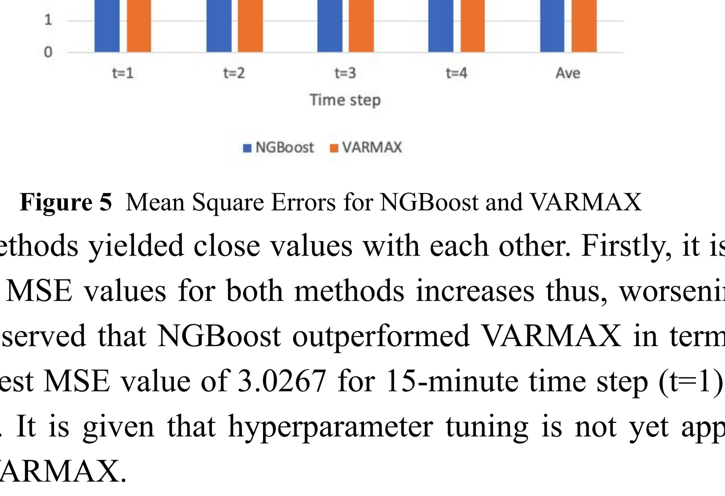

Figure 5 Mean Square Errors for NGBoost and VARMAX

In figure 5, the two methods yielded close values with each other. Firstly, it is observed that as further the time steps, MSE values for both methods increases thus, worsening the prediction. Secondly, it is also observed that NGBoost outperformed VARMAX in terms of MSE where NGBoost gave its lowest MSE value of 3.0267 for 15-minute time step (t=1) vs MSE value of 4.1162 for VARMAX. It is given that hyperparameter tuning is not yet applied to NGBoost while it is applied in VARMAX.

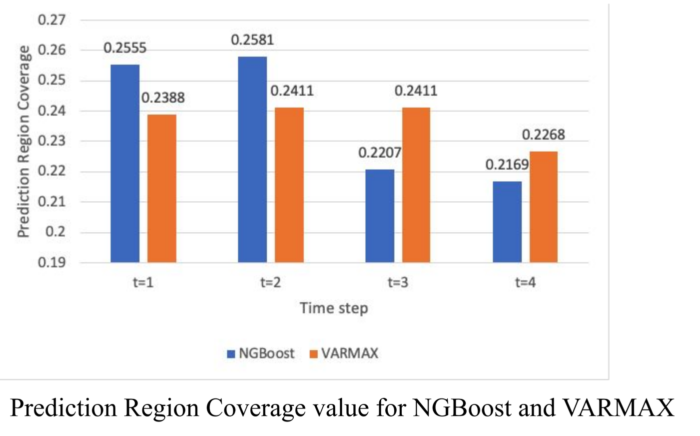

Figure 6 Prediction Region Coverage value for NGBoost and VARMAX

Based on α% values 0.25 for NGBoost and 0.75 for VARMAX that was set arbitrarily, and used for comparison purposes, the prediction intervals region coverage values were obtained. As observed in table 3, both methods produced close values with each other. It is also noticed that for prediction region coverage values for NGBoost where its value decreases for each time step. However, VARMAX produced almost no patterns throughout time steps wherein it got a prediction region percentage value of 0.2411 for both t = 2 and t = 3. But in average, both methods produced very close values.

REFERENCES

1. A. A. Muzumdar, C. N. Modi, M. G. M, and C. Vyjayanthi, "Designing a robust and accurate model for consumer centric short term load forecasting in Microgrid Environment," IEEE Systems Journal, pp. 1–12, 2021.
2. E. Lucas Segarra, G. Ramos Ruiz, and C. Fern´andez Bandera, "Probabilistic Load Forecasting for building energy models," Sensors, vol. 20, no. 22, p. 6525, 2020.
3. A. Yousaf, R. M. Asif, M. Shakir, A. U. Rehman, and M. S. Adrees, "An improved residential electricity load forecasting using a machine-learning-based feature selection approach and a proposed integration strategy," Sustainability, vol. 13, no. 11, p. 6199, 2021.
4. T. Duan et al., "NGBoost: Natural Gradient Boosting for Probabilistic Prediction," arXiv:1910.03225v4 [cs.LG] 9 Jun. 2020.
5. M. O'Malley, A. M. Sykulski, R. Lumpkin, and A. Schuler, "Multivariate Probabilistic Regression with Natural Gradient Boosting," arXiv:2106.03823v1 [stat.ML] 7 Jun. 2021.
6. S. Silwal, C. Mullican, Y.-A. Chen, A. Ghosh, J. Dilliott, and J. Kleissl, 2021, "Open-source multi year power generation, consumption, and storage data in a microgrid," Journal of Renewable and Sustainable Energy, vol. 13, no. 2, p. 025301.
7. S. Seabold and J. Perktold, 2010, "statsmodels: Econometric and statistical modeling with python," in 9th Python in Science Conference

ACKNOWLEDGEMENT

We would like to acknowledge ERDT for continual scholarship for Master of Science in Computer Science of UP Diliman as well as the support of Computer Vision and Machine Intelligence Group