

Energy Demand Prediction Combining Solar and Smart Meter Data Using XGBoost Algorithm

G S BIBIN ¹, H VENNILA. ², D. SHINEYMANOJ.³, M. CHINCHU.⁴
and TIBBIE PON SYMON VA. ⁵

¹ Research Scholar, Department of EEE, Noorul Islam Centre for Higher Education, Tamil Nadu, India

² Associate Professor, Department of EEE, Noorul Islam Centre for Higher Education, Tamil Nadu, India

³ Assistant Professor, Department of Physics, Christian College Kattakada, Kerala, India

⁴ Assistant Professor, College of Engineering Kidangoor, Kerala, India

⁵ Professor, Department of EEE, Mar Baselios Institute of Technology & Science, Kerala, India

Mail id: bibings81@gmail.com, vennilarajesh@yahoo.co.in, drshineymanoj@gmail.com, chinchubibin13@gmail.com, tibbiesymon@gmail.com,

Abstract— Energy demand prediction in the recent years has become highly Complex due to the penetration of volatile solar photovoltaic generation and electric vehicle charging. This volatile parameter has highly affected the accuracy of electricity demand prediction. Even with the latest prediction algorithms we find it challenging to find the accurate results. A study exploring the use of precision smart meter data along with solar generation is proposed. These data with extreme gradient boosting machine learning algorithm have yielded better results. The generation data along with the consumption needs to be analysed along with traditional variables. Earlier we have used various statistical techniques like ARIMA and random forest algorithms which has given less accurate results. The results obtained in the proposed model are evaluated using error matrices like mean absolute error (MAE) and root mean square error (RMSE). The proposed XGBoost model has improved MAE and RMSE than other machine learning techniques.

Keywords— “Energy demand prediction”, “solar data”, “XG boost machine learning”, “RMSE”, “MAE”

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I. INTRODUCTION

1.1 Background

The operation of any electrical utility is based on financial viability. The profitability of operation makes the companies to sustain and grow. Hence the accurate demand prediction helps the energy utilities in Operation like planning, scheduling etc. The accurate demand prediction will lower the cost of operation. Apart from the traditional Forecasting models where the historical data has been relied, here in this model highly accurate real time data from solar generators and smart metering systems are made use of. [1][2]

1.2 Research problem

The factors affecting the demand are user patterns, the climatic conditions and the Solar photovoltaic generation. Consumer patterns can be analysed from historical data and seasonal data. Load patterns from smart meter gives a window picture of real time usage. The Solar photovoltaic generation largely depends on solar irradiation, so the prediction of solar photovoltaic generation poses a serious gap in accurate demand forecasting. This is overcome by using hybrid models that uses data from different sources [3]

1.3 Objectives

The objective is to model an XG boost based demand forecasting algorithm using smart meter data and Solar photovoltaic generation to obtain highly accurate demand prediction [4][5]

Specific goals

- preprocess multisource data

- Train and validate XGBoost model
- compare evaluation matrices

2. LITERATURE REVIEW

Over the years various energy demand forecasting models are developed. It extends from various mathematical models to different machine learning techniques. Various weather variables such as temperature, humidity and solar irradiance have been incorporated in the recent studies. The direct integration of solar data with real time energy consumption needs to be explored. Such a gap is explored using XG boost algorithm

Paterakis et.al in this study investigates deep learning (DL) methods, which are more sophisticated than typical machine learning (ML) approaches. Even though a variety of ML techniques have been utilised for probabilistic prediction, DL techniques undoubtedly showcase the most advanced AI techniques with notable success in a range of real-world applications [6].

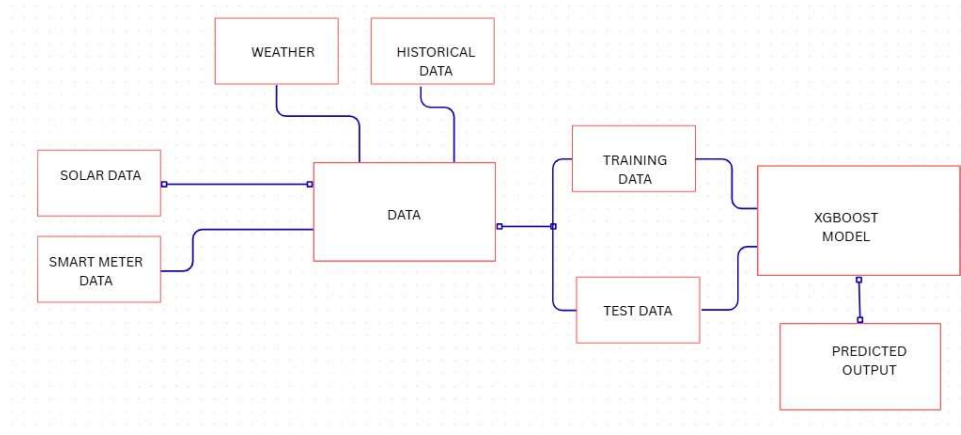
Bedi et al. offers an empirical mode decomposition (EMD)-based deep learning

strategy to investigate electricity demand for the given season. A load time series signal is broken down into many intrinsic mode functions (IMFs) and residual using the EMD algorithm. Next, a distinct LSTM model is trained for every extracted IMF and residual. Ultimately, an aggregate output for power demand is calculated by summing the projection findings of all IMFs.[7]

Shin J et.al, introduces a novel architecture that emphasizes the crucial role preprocessing plays in enhancing prediction performance. Data preparation, process optimization techniques, and prediction are the three main pillars of the architecture, which identifies patterns suggestive of time series characteristics. [8]

Yan et.al proposes a hybrid deep learning neural network framework that blends convolutional neural network (CNN) with LSTM is presented to further increase the prediction accuracy. To increase response time for power market bidding, short-term forecasting technique is extended to a multi-level forecasting model.[9]

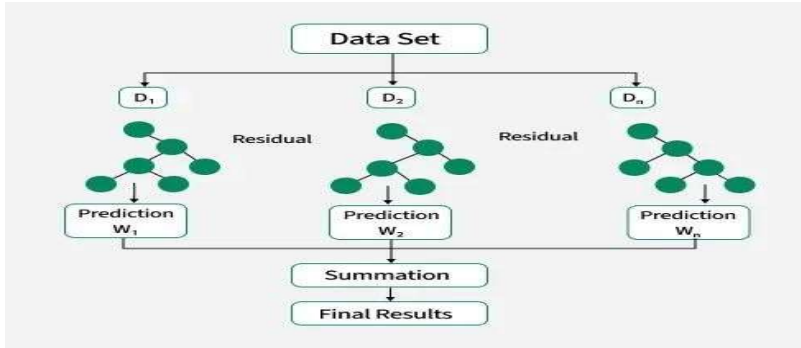
3. METHODOLOGY



Our data set consists of four types of data namely solar data, smart meter data, weather data, and historical data. These data help our prediction process in order to get a better forecasting. The entire data received is divided into training and test data .80% of the data is used for the training process. And the rest for testing process. Using the training data we train the XGBOOST model and then the model is ready for testing. A block diagram of the proposed method is given above in fig.[10][11]

3.2 Model development

XG boost model



XT boost is an optimised gradient boosting algorithm. It has high speed and good performance the important highlights of using this model are

- Higher Learning rate
- Better accuracy

3.2 Evaluation mattress

The performance of the XG boost algorithm can be evaluated by analysing the performance matrices such as mean absolute error (MAE) and root mean squared error (RMSE)

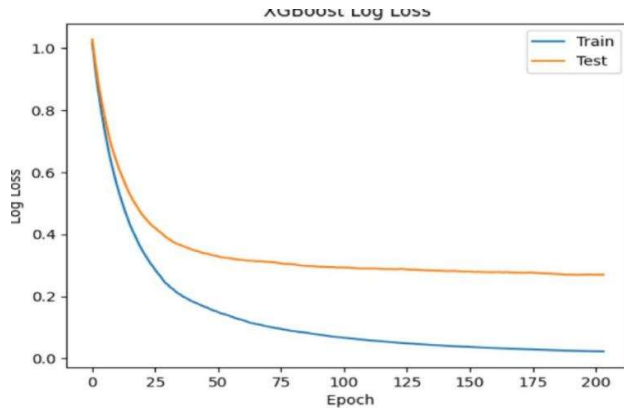
$$RMSE = \sqrt{\frac{\sum (y_i - y_p)^2}{n}}$$

$$MAE = \frac{|(y_i - y_p)|}{n}$$

y_i = actual value
 y_p = predicted value
 n = number of observations/rows

3.3 Training

The data set are collected for a period of 1 year. The various weather variables are also collected during the period. The Solar photovoltaic data as well as the real time solar smart metre data is also utilised for training. 70% of this data is used for training and the rest is used for validation and testing purpose [12]

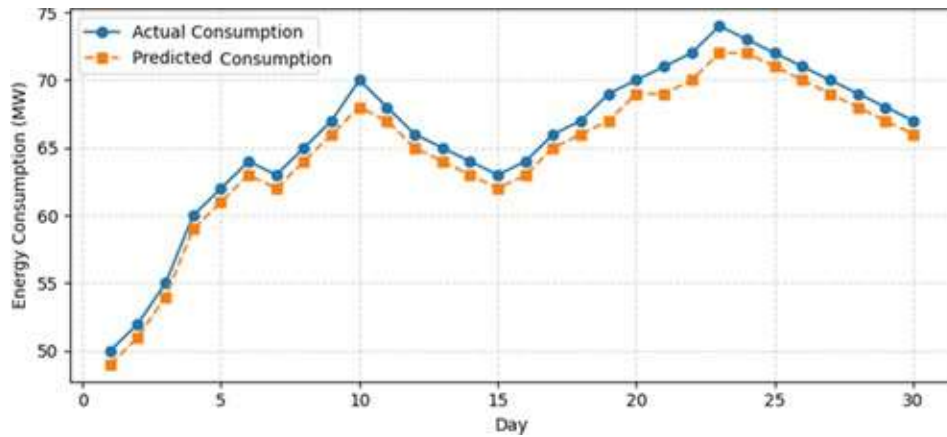


4. PERFORMANCE COMPARISON

ALGORITHM	MAE	RMSE
Random forest	2.15	2.7
LSTM	2	2.5
XGBoost	1.72	2.15

4.1 Interpretation of results

The performance of XG boost specifies effectiveness of the model while combining the solar photovoltaic generation and the real time smart meter data.



5 CONCLUSION

The study focusses on a demand forecasting network combining the environment and historical parameters along with solar photovoltaic generation and the real time smart meter data. Results demonstrate the superiority of integrating multi source data using XGBoost model. The proposed model achieves higher accuracy compared to other existing models. This model can contribute much to efficient operation and encourage the financial stability of energy

utilities worldwide. Compared to standalone deep learning models and conventional statistical techniques, the suggested model greatly increases in predicting demand with higher accuracy. The proposed model regularly outperforms benchmark techniques like ARIMA, SVR, persistence models, and standard LSTM, especially in multi-step forecasting scenarios, according to experimental results . Overall, the

study indicates that hybrid deep learning architectures offer a viable and scalable option for accurate short-term power consumption forecasting in smart grid situations.

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