Energy Generation Forecasting Based on Seasonality Using Deep Learning

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doi: https://doi.org/10.21467/proceedings.141.5

ABSTRACT

Energy forecasting is affected by various factors like seasonality, abrupt weather changes, system malfunctions, and lack of efficient resource management. Hence, towards meeting the energy demand of consumers, there is a need to generate energy efficiently which can be from renewable or nonrenewable sources like coal, wind, solar etc. This requires the need of machine learning and deep learning technique to forecast the generation of energy efficiently and economically. This work focuses on solving the issue related to energy generation forecasting by analyzing energy generation from various fuel sources over the course of 8 years by applying various techniques such as Bi-LSTM, Nbeats, ETS, Xgboost and MLP. From the performance analysis for the four seasons, it has been concluded that Bi-LSTM performed the best overall in the 4 seasons with an average SMAPE of 20.412. This would really benefit utility companies in forecasting the fuel generation effectively in meeting the consumer demand.

Keywords: renewable, non-renewable, machine learning, deep learning.

1 Introduction

Energy forecasting is an essential component of efficient scheduling and distribution systems in the energy sector. It is used to inform industry stakeholders of appropriate distribution management to consumers as well as in electricity generation to manage surplus. This is enabled by providing valuable information about the expected changes in the energy to be generated in the near future. Energy forecasting includes forecasting demand, generation and price of electricity, fossil fuels and renewable energy sources. A useful approach for this problem is time series forecasting, as energy generation data is typically stored in the form of historical time-stamped data. There has been some work done in the part towards energy productions and demand forecasting using machine learning which are briefed here.

The w in [1] discussed the effectiveness of machine learning models in forecasting energy production. The results of the paper show that a combination of machine learning and statistical models produces the best results. The second aspect of the paper deals with feature extraction. The authors propose a two-step process. First, to perform the filtering, the Pearson correlation coefficient is used to find a filtered subset. Secondly, the authors propose a wrapper on the filtered subset. For this, the authors use an LSTM model to find the subset of filtered features which produce the lowest RMSE. These features become the final set used for training. The total feature selection process is carried out using a technique called multimodal ensemble feature selection.

Proceedings DOI: 10.21467/proceedings.141; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-957605-4-1

As reported in [2], the work applied deep learning for forecasting energy consumption wherein the data is taken from two tenants of a commercial building. Three methodologies: “Support Vector Machine, Artificial Neural Network, and k-Nearest Neighbours”, are proposed for the algorithm of the predictive model. The model performance is compared based on “RMSE, NRMSE, and MAPE” metrics. The tenant’s energy consumption has different distribution characteristics based on experiment. “SVMs” were able to achieve the lowest “RMSE” of 4.7506789 and 3.5898263 for the two tenants however this came at a cost of high training times of up to 13-14 hours. Authors in [3] have worked towards electrical power load forecasting by analysing the pattern of electrical load and predicting the future of electrical load demand for short, medium, and long term. The authors here have applied time series methodology and forecasting was conducted for daily electrical power load based on Kuwait electricity network for three years. Authors in [4] have worked towards electricity demand prediction reliably using “Adaptive Neuro Fuzzy Inference System (ANFIS)”. The focus of the work was considered towards electrical load forecasting for medium term in a “Greater Accra” Region of “Mallam” town which is densely populated. From the validation, it was proved that “ANFIS” prediction model is dependent on quality of data and tuning parameters. Authors in [5] have worked on yearly electricity demand forecast of Bangladesh using “multivariate time series”. The authors in this work have introduced two exogenous variables which are Population and “GDP”. “Autoregressive Integrated Moving Average” with Exogenous which is “ARIMAX (0,1,1)” that show comparatively better performance than the state of art model with the lowest “Alkaline Information Criterion (AIC)” values.

From the literature review, it is clear that there has been limited work done on energy generation and demand forecasting using machine learning and deep learning technique. Hence, this work focuses on predicting the energy generation in terms of Mega Watt Hours (MWh). The major focus of the paper is to predict energy generation from different fuel sources like coal, solar, wind, etc. This forecast would enable stakeholders to meet projected energy demands by maximizing the use of sustainable energy sources like wind and solar while minimizing the usage of fossil fuels. Another aspect being tackled in this paper is the seasonal variation in energy generation. This implies that forecasting methods should not just capture the global trend but also understand the local (seasonal) trends. With the help of machine learning and deep learning techniques, this work is able to forecast the energy generated by a facility given the facility’s previous energy Output forecasting models such as LSTMs and recently introduced NBEATs models are able to achieve great results in forecasting the energy generated by each facility. These models were able to leverage trends such as differences in season-wise generation of energy and even differences in day and night-time generation of energy.

The rest of paper is organized as follows. Section 2 gives a description of the methodology used for implementation pertaining to models used Section 3 gives details on results and discussion. Section 4 concludes the paper.

2 Materials and Methods

A time series is a collection of data that has been observed over time. The goal of time series analysis is to look at the path of time series observations, develop a model to describe the data structure, and then forecast the future values of time series. To establish a statistical baseline, Exponential smoothing (ES) [6] with its three variants Simple ES [7], Double ES [8] and Tripe ES [9] were used. Also, XGBoost [10] was used to provide a baseline for gradient boosted models. Post this, deep learning algorithms were used. To measure baseline performance for this, the multi-layer perceptron (MLP) [11] was used. In addition, more recent architectures such as Bi-LSTM [12] and Nbeats [13] were also used. Details on models used are explained below.

2.1 Exponential Triple Smoothing:

Among the three variants of ES, Triple ES was implemented as it was found to be the superior one. The model was implemented with an additive trend component. Training was performed with the evaluation metric as root mean squared error. The additive model is useful when the seasonal variation is relatively constant over time and the trend seems more linear.

2.2 XGBoost:

The model was instantiated with 500 estimators, with the objective set as regression with squared loss. Training was performed with the evaluation metric as root mean squared error and an evaluation set was provided to fit the model.

2.3 Multi-Layer Perceptron (MLP):

The Multilayer Perceptron was created with an input layer of input data dimensions, Dense layer of 32 units and ReLU activation function as the hidden layer, followed by another Dense layer of 1 unit as the output layer, with Mean squared error as loss and Adam optimiser. Training was initially set for 1000 epochs with call backs for Early Stopping and Learning Rate Reduction, on a batch size of 4 with no shuffling of data points.

2.4 Bi-LSTM:

The Bidirectional LSTM or biLSTM is an improved or enhanced form of LSTM. Information travels from backward to forward in unidirectional LSTMs, but bi-directional LSTMs use hidden states to transmit information from backward to forward and forward to backward. To train the Bi-LSTM, Adam optimizer was used with Mean Squared Error (MSE) as the loss function. The training was performed over 1000 epochs, with a validation split of 20% and the Root Mean Squared Error (RMSE) used as the metric. The batch size was set to 128 with no shuffling of data points since this method is dealing with time-series data. Furthermore, early stopping was used with the patience factor set to 10 while monitoring validation loss.

2.5 NBeats:

The NBeats model was created using the DARTS library in python with 10 stacks with 1 NBeats block in each stack. Totally 4 such layers were used with the layer width being 512 and the expansion coefficient dimension was set to 5. The input chunk length was 30 and the output chunk length was set to 7. The model was trained for 100 epochs with a batch size of 128. RMSE was used as the metric. Figure 1 shows the architecture of Nbeats.

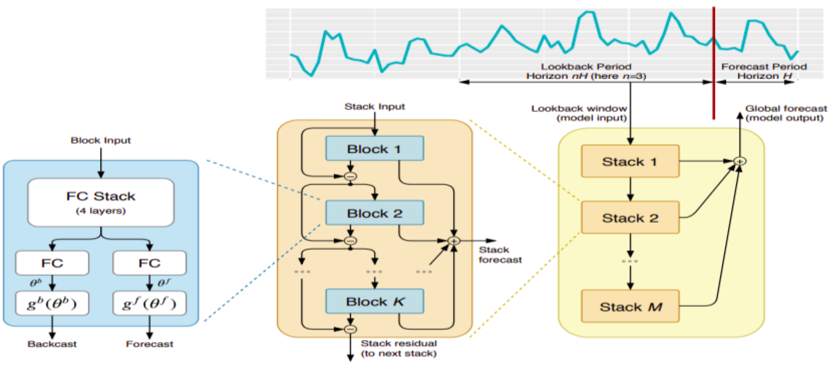

Figure 1: *Architecture of Nbeats.*

3 Theory and Calculation

The data for this study was sourced from: "http://data.wa.aemo.com.au/#facility-scada" and "http://data.wa.aemo.com.au/#commissioning-test". It contains Australian energy market information as time series data of energy generation measured in MegaWatt hour (MWh), indexed by time-stamp and recorded every 30 mins. The dataset for training the models was created by merging facility data which contained the time-stamped values of energy generation, and commission data which contained the fuel type, both mapped by both a 'Facility Code' and a 'Participant Code'. The data has been divided into seasons as follows:

A. Season_1 = Dec 2020-Feb 2021
B. Season_2 = March-May 2021
C. Season_3 = June-Aug 2021
D. Season_4 = Sept to Nov 2021

Table 1 describes the characteristics of the data, while Figure 2 depicts the fluctuation in energy generation across the observed period of 4 years from July 2017 to July 2021

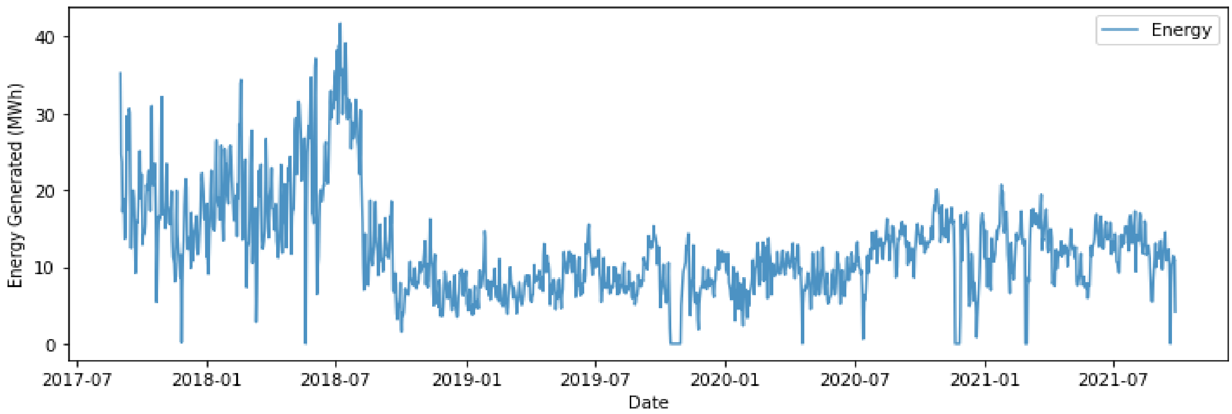

Figure 2: *Energy generation from 2017-2021.*

Table 1: *Summary of statistical metrics of the data*

Measure	Value
count	1487.000
mean	12.290
std	6.502
min	0.000
25%	7.833
50%	11.246
75%	14.994
max	41.716

The Augmented Dickey-Fuller test is used to test the statistical significance of the hypothesis tests [14]. Using the resulting p-value, one can conclude if the time series data is stationary or not. From the Augmented Dickey-Fuller Test, p-value obtained is very low at 0.001941. A small p-value ($p<0.05$) indicates strong evidence against the null hypothesis. Therefore, the null hypothesis is rejected. This dataset appears to have no unit root and is stationary. To measure the results, the data was split into 4 seasons and results for each season were measured for each algorithm. The graph below summarizes the key findings and plots the SMAPE value for each algorithm for each season as shown in Figure 3 and Table-3.

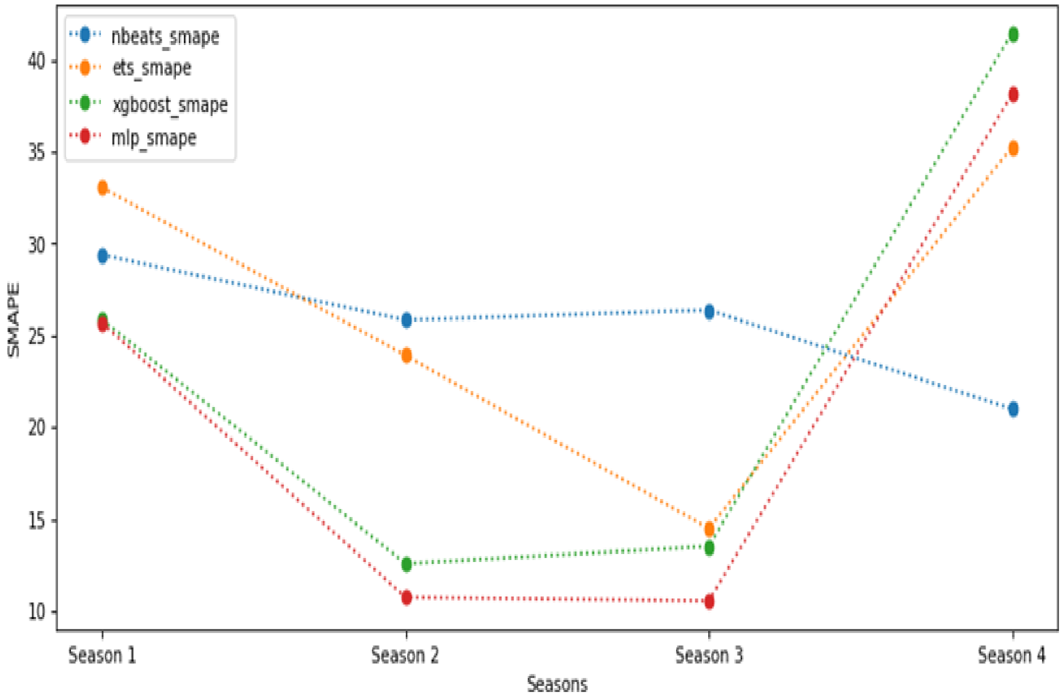

Figure 3: *Model comparison by SMAPE score*

Table 2: *Average SMAPE values over 4 seasons for each algorithm*

Algorithm	Value
Bi-LSTM	20.412
MLP	21.278
XGBoost	23.360
Nbeats	25.648
ETS	26.679

From Figure 3 and Table 2, it is seen that the Bi-LSTM model has the best average performance over all 4 seasons. In the below section, metrics for the Bi-LSTM model for each season is tabulated in Table 3 and the respective truth vs prediction graphs are plotted in Figures 4 to 8.

Proceedings DOI: 10.21467/proceedings.141
ISBN: 978-81-957605-4-1

Series: AIJR Proceedings
ISSN: 2582-3922

Table 3: *Metrics of Bi-LSTM over each season*

Season	SMAPE	RMSE	MSE	MAE
1	25.1900	3.0731	9.4439	2.3488
2	18.5200	2.6721	7.1401	1.9937
3	14.5800	2.1500	4.6225	1.7958
4	23.3600	3.4007	11.5647	2.1512

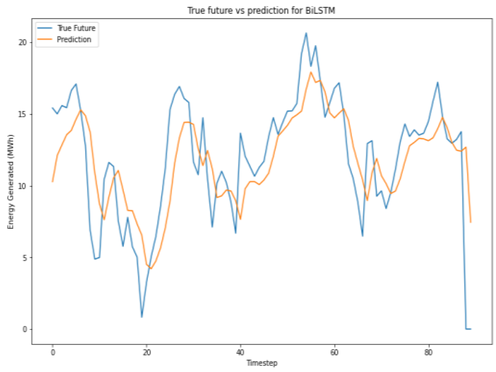

Figure 4: *Season 1 true vs predicted values*

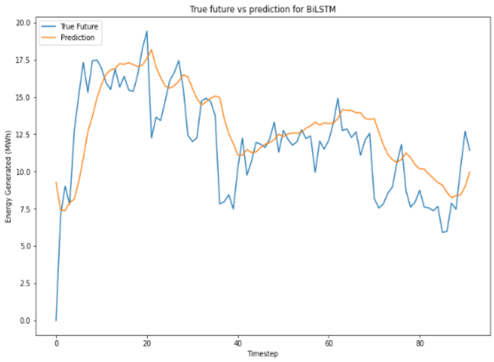

Figure 5: *Season 2 true vs predicted values*

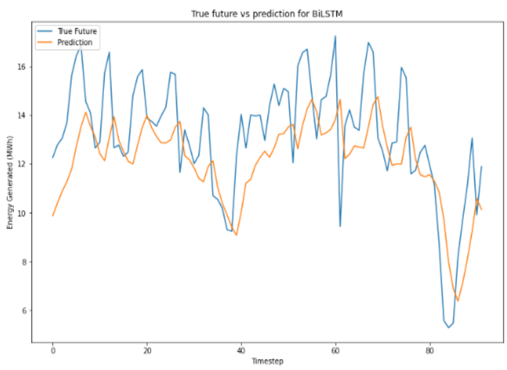

Figure 6: *Season 3 true vs predicted values*

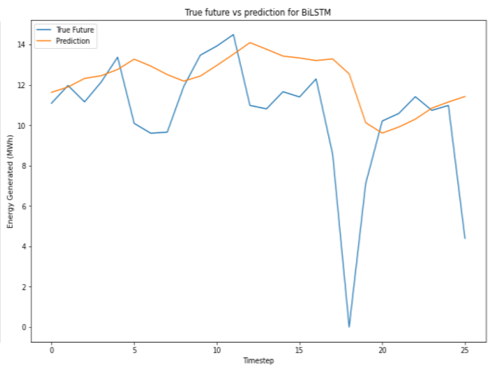

Figure 7: *Season 4 true vs predicted values*

From Figure 4, in Season 1, it can be inferred that the model is able to capture the trends to a sufficient level but has a certain lag in capture. Then, from Figure 5, in Season 2, it is observed that the model is underfit since the model is not able to capture the underlying complexity in the trend to sufficient degree. A similar statement could be made for Season 3 in Figure 6. Finally, for season 4, Figure 7 shows poor performance of the model where the underlying pattern is not captured.

4 Conclusion

In this paper, several methods such as statistical, machine learning and deep learning methods are applied to compute energy generation. Through the lens of developing different models for different seasons, this work was able to measure which model performed best for each season. On average, Bi-LSTM performed the best overall 4 seasons with an average SMAPE of 20.412. To handle seasonal variation, the best performing models for each season can be used or alternatively, an ensemble of all the models can be used as future work. Besides that, the energy generation can be correlated with consumer demand and price forecast as which energy generation is economical during peak and non-peak hour to handle consumer demand and price efficiently. In future, optimization of algorithms can be done to further improve the forecasting accuracy.

5 Declarations

5.1 Acknowledgements

This research was done in collaboration with the Universiti Malaya, Malaysia as a part of SATU Joint Research Scheme and funded by Research Grant from Universiti Malaya (Project Number ST005-2021). In addition, we like to thank SRMIST for providing AWS Cloud support for finishing the project work.

5.2 Competing Interests

There have been no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

5.3 Publisher’s Note

AIJR remains neutral with regard to jurisdiction claims in published maps and institutional affiliations.

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