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Machine Learning Algorithms for Electricity Load Demand Forecasting: A Snapshot of Abuja

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Abstract: *Load forecasting is one of the most reliable strategies for improving or facilitating effective planning, suitable operation, and adequate management of surges in electrical energy demand. Load forecasting is an integral part of electric power operation, planning, and maintenance. Machine learning algorithms have been applied in several fields of engineering to forecast quantities with a higher degree of accuracy when compared to other techniques. In this work, Machine Leaning algorithms: Feed Forward Neural Network (FNNN) and Long Short-Term Memory (LSTM) were used to forecast load demand in Abuja, Nigeria. The data was obtained from Photovoltaic Geographical Information System. Data for fifteen years was obtained, it was divided into three parts modeling, thirteen years for training, one year for validation, and one year for testing. Two techniques of cross-validation were utilized to guarantee there was no overfitting or underfitting in the training, validation, and testing data. Results showed that FNNN performed better than LSTM based on RMSE and MAE. The RMSE of LSTM and FFNN, on average, was found to be 110.81 and 104.34, respectively. The MAE for LSTM and FNNN was found to be 57.08 and 55.04, respectively. The persistence model consistently performs poorly in all cases. As a result, solar irradiance from the previous day has a minimal correlation with solar irradiance from the day ahead.*

Keywords: *Machine Learning, Forecasting, Load demand, Feed Forward Neural Network, Long Short-Term Memory*

INTRODUCTION

Load forecasting has been adjudged to be a vital tool for the proper operation of electric power systems to enhance the system efficiency, and stability, reduce operating costs and maintain the demand and supply equilibrium (Dong *et al.*, 2021). The rapid growth of Distributed Energy Resources (DER) including solar systems, and battery storage devices all over the world with the aim of fast-tracking the deployment of renewable energy both in developing and advanced countries has been receiving tremendous attention. This trend is intended to accelerate the adoption of renewable energy into the traditional energy mix. As a result, load forecasting has become central to achieving this aim(Sethi and Kleissl, 2020). During periods of excess renewable generation (low demand), storage devices can store excess energy, which can then be discharged during periods of high demand (Al Shaqsi *et al.*, 2020).

An Energy Management System is required for the integration of DER. This can help lower load peaks, allowing the utility to keep the system running during peak hours. Customers can save money by lowering their demand costs (Cambini *et al.*, 2020). A fundamental component of this Energy Management System is forecasting future load demand which has one of its core functions being the control of the battery system in terms of charging and discharging at the appropriate time. As a result, a reliable short-term load forecasting model is necessary. The most common application of short-term load forecasting is to predict load values for the next few hours to days (Negnevitsky *et. al.*, 2009). The energy supply must be effectively regulated to maintain a sustainable trend in a developing sector. Many studies are currently concentrating on forecasting electrical energy for closed and open systems using mathematical approaches, classical statistics, and artificial intelligence systems. However, demand is difficult to forecast because it is linked to economic growth and population growth(Kim and Cho, 2019).

Some of the fundamental factors that affect energy usage include weather, the hour of the day, the time of year, increase in the population (Abba *et al.*, 2021). Load forecasting could be broadly classified into three types based on the duration. These are Short-term (STLF), medium- (MTLF), and long-term load forecasting (LTLF) techniques. STLF is a one-hour to one-week load forecast; MTLF is a one-week to one-year load prediction; and LTLF is a one-year to approximately ten-year load forecast(Olabode *et al.*, 2020). STLF is beneficial in terms of enhanced economic savings as well as improved power system security; MTLF is also relevant. Multiple regression, moving average with exogenous variable (ARMAX), exponential smoothing, iterative reweighted least-squares, adaptive load forecasting, autoregressive, genetic algorithms, artificial neural networks, stochastic time series, and knowledge-based expert systems, fuzzy logic, are just a few of the approaches and models that can be used to forecast energy in power systems engineering (Wang *et al*, 2018; Elijah *et. al*, 2019; Wei *et al.*, 2019). Several works have already devoted enough time to implement most of the algorithms stated. A comprehensive review of such applications could be found in (Guefano *et al.*, 2021). One of the most recent research is reported by (Amber *et al.*, 2018), which conducted a comparative analysis on the preliminary capacities of five model types while projecting the need for an administrative building in London, United Kingdom. The five approaches are deep neural networks, multiple regression, genetic programming, support vector machines, and artificial neural networks. ANN with an error of 6% outperforms all the other models, which have average errors of 8:5 percent, 8:7 percent, 9 percent, and 11 percent for deep neural networks, multiple regression, genetic programming, and support vector machines respectively. In this work, two ANN-based algorithms were developed to forecast load demand in Abuja, Nigeria. The data was obtained from Photovoltaic Geographical Information System.

MATERIALS AND METHODS

The background theory behind the models adopted is presented here. We will begin with a general background in deep learning. FFNN and LSTM-RNN are then introduced.

A. Deep Learning

Deep learning has been getting a lot of attention due to its ability to deploy multiple layers of processing information in several areas of engineering such as classification, prediction, etc. (Bengio, 2009). It deploys the backpropagation algorithm to continuously update the weights of the neurons in the layers so as achieve better results (Xin *et al.*, 2018). Convolutional Neural Networks (CNN), FFNN, RNN, and Autoencoders, are examples of deep learning architectures. The FFNN and RNN architectures are the most extensively utilized among these architectures (Hosseini *et al.*, 2020). CNN is a form of FFNN that is great at processing movies and audio. LSTMs, are a form of RNN. They are particularly good at processing data like audio, and time series data. Deep learning is fast advancing in a range of fields.

It outperforms other machine learning algorithms in picture recognition (Krizhevsky, *et. al*, 2012), speech recognition (Sainath *et al.*, 2013), natural language understanding(Collobert *et al.*, 2011), language translation (Jean *et al.*, 2014), particle accelerator data analysis (Ciodaro *et al.*, 2012), potential drug molecule activity prediction(Ma *et al.*, 2015), and brain circuit reconstruction (Helmstaedter *et al.*, 2013). However, its use in predicting solar irradiance is limited(Paulescu and Paulescu, 2019).

B. Feedforward Neural Network

As shown in Fig. 1 the architecture of an FFNN consists of three layers: input layer, hidden layer, and output layers. The input layer is connected to the hidden layer and the hidden layer to the output layer. The inputs and output to the FFNN are taken from the input and output layers respectively. The output layer makes the decision (prediction or classification etc.) based on the output from the hidden layer where the computations take place. We can generate M linear combinations of the input variables x_1, x_D for the FFNN in Fig. 1 in the form:

$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} \cdot x_i + b_j^{(1)} \tag{1}$$

where,

$j = 1, \ldots, M$

The superscript (1) in Eq. (1) indicates that corresponding parameters are in the first layer of the network $w_{ji}^{(1)}$, and $b_j^{(1)}$ are the weights and biases; j and M are the index and the total number of the linear combination of the input variables, respectively; i and D are the index and the total number of the input variables, respectively; a_j is the activation. The output unit activations are converted using an activation function to give the model outputs yk.

$$y_k(\mathrm{X},\mathrm{W}) = \sigma\left(\sum_{j=1}^{M} w_{kj}^{(2)} h\left(\sum_{i=1}^{D} w_{ji}^{(1)} \cdot x_i + b_j^{(1)}\right) + b_k^{(2)}\right) \tag{2}$$

In summary, the FFNN model is a nonlinear function from a set of input variables {xi}s to a set of output variables {yk} controlled by a vector W of adjustable parameters (Husein and Chung, 2019).

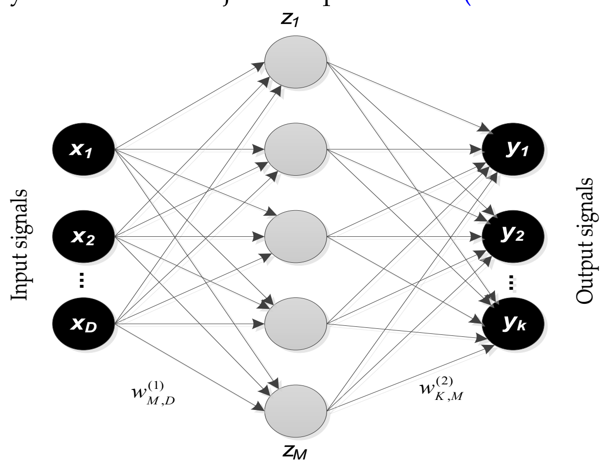

Fig. 1 Feedforward neural network (FFNN) (Husein and Chung, 2019)

C. Long Short-Term Memory Recurrent Neural Network

RNN is a form of ANN where the learning takes place at every single element of a given sequence this has the added advantage of making the output a result of several computations from all the elements thus making it robust. Given an input sequence x = (x_1, …, x_T), standard RNNs compute the hidden vector sequence h = (h_1, …, h_T) and output vector sequence y = (y_1, …, y_T) by iterating Eq. (3) and (4) from t = 1 to T:

$$h_t = H(W_{xh} \cdot x_t + W_{hh} \cdot h_{t-1} + b_h) \quad (3)$$

$$y_t = W_{hy} \cdot h_t + b_y \quad (4)$$

where W_{xh}, denotes input-hidden, W_{hh} is hidden-hidden W_{hy} hidden-output weight terms respectively. The b_h and by terms denote hidden and output bias vectors, respectively. The hidden layer activation function is denoted by the letter H. The sigmoid function is normally applied element by element. Fig. 2 depicts the forward computation of an RNN network as it unfolds over time. Other neurons from prior time steps provide input to the artificial neurons.

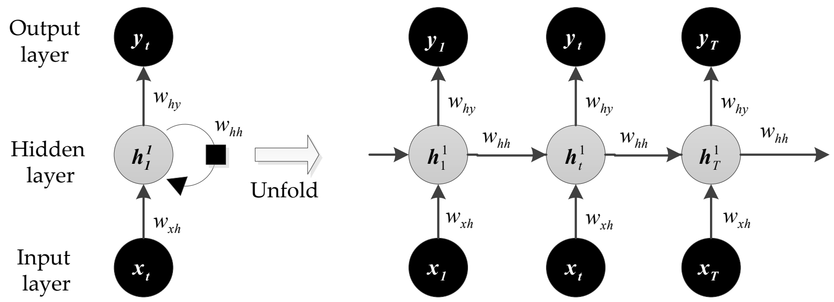

Fig. 2 Recurrent neural network (RNN)

In comparison to other models, RNNs have a feedback mechanism to help increase accuracy (Chen *et al.*, 2018). Their output is determined by the network's current input as well as prior inputs or outputs. RNNs are extremely powerful dynamic systems, but training them has proven problematic because backpropagated gradients rise or shrink at each time step, causing them to burst or vanish across multiple time steps (Watt and du Plessis, 2018). One possibility for solving this problem is to make provision for dedicated memory. The LSTM has been the first to address this problem (Izadyar *et al.*, 2016).

D. Model Formulation

This section presents a model for projecting the global horizontal irradiance (GHI) during 24 hours. Because GHI is the irradiance falling on a horizontal surface, and PV arrays are often positioned inclined to the horizontal plane, we must account for this inclination when calculating solar irradiance incident on the PV array. A variety of models of varying complexity have been proposed for determining incident sun irradiation. The HDKR model is the most extensively utilized of these models. Equation (7) below shows how to calculate the outcomes (Duffie, *et. al*, 2020).

$$G_{inc} = (G_b + G_d \cdot A_i) \cdot R_b + G_d(1 - A_i) \cdot \left(\frac{1+\cos\beta}{2}\right) \cdot \left(1 + f \cdot \sin^3\left(\frac{\beta}{2}\right)\right) + G \cdot \rho_g \left(\frac{1-\cos\beta}{2}\right) \quad (5)$$

where G is the GHI, Gb is the beam radiation, Gd is the diffuse radiation,β is the surface slope in degrees, is the ground reflectance, R_b is the ratio of the slanted surface beam radiation to the horizontal surface beam radiation, and Ai denotes the anisotropy index, which is a function of the atmosphere's transmittance for beam radiation, and f is the cloudiness factor. From the incident irradiance determined in Eq. (6), the power produced by the PV modules may be computed as follows: (Duffie, *et. al*, 2020):

$$P_{pv} = P_{pv,STC} \cdot \frac{G_{inc}}{G_{inc,STC}} [1 + k_T \cdot (T_{cell} - T_{cell,STC})] \quad (6)$$

where $P_{pv,STC}$ is the rated PV power at standard test conditions (kW), kT is the temperature coefficient of power (%/°C), T_{cell} is the PV cell temperature (°C), $T_{cell,STC}$ is the PV cell temperature at standard test conditions (25 °C), $G_{inc,STC}$ is the incident solar irradiance at standard test conditions (1 kW/m2), and G_{inc} is the incident solar irradiance on the plane of the PV array (kW/m2). The cell temperature, T_{cell}, is calculated in Eq. (7):

$$T_{cell} = T_{amb} + \frac{G_{inc}}{800} \cdot [NOCT - 20] \tag{7}$$

where T_{amb} is the ambient temperature and NOCT is an acronym for the nominal operating cell temperature, a constant that is defined under the ambient temperature of 20 °C, incident solar irradiance of 800 W/m2, and wind speed of 1 m/s.

E. Data Description

The data for this study was obtained from PVGIS Photovoltaic Geographical Information System under the Joint Research Centre (JRC) of the European Commission's science and knowledge service. The data repository used is free and contains data for several continents (PVGIS, 2018). Nigeria's electricity demand is expected to increase by 16.8 times by 2030, from 77,450 megawatts in 2025 to 119,200 megawatts in 2030(Abba *et al.*, 2021). The current research was carried out at Abuja, Nigeria's capital, which is located at the confluence of the Niger and Benue rivers. Data for fifteen years was obtained, it was divided into three parts modeling, thirteen years for training, one year for validation, and one year for testing. Two techniques of cross-validation were utilized to guarantee there was no overfitting or underfitting in the training, validation, and testing data.

F. Performance Metrics

Determining the accuracy of machine learning models requires the utilization of widely acceptable metrics that are simple and robust. As indicated in (Najashi and Feng, 2014), there are numerous issues to consider when selecting a measure. Research has shown that in some cases, the metrics used can provide inaccurate or misleading results. Notwithstanding, there has been a consensus that root means square error (RMSE) and mean absolute error (MAE) are the commonly adopted metrics in the literature. Equations (8) and (9) are used to calculate the RMSE and MAE, respectively.

$$RMSE = \sqrt{\frac{1}{T \cdot M}\sum_{i=1}^{M}\sum_{t=1}^{T}(h(x_t^{(i)}) - y_t^{(i)})^2} \tag{8}$$

$$MAE = \frac{1}{T \cdot M}\sum_{i=1}^{M}\sum_{t=1}^{T}\left|(h(x_t^{(i)}) - y_t^{(i)})\right| \tag{9}$$

M is the number of examples in the dataset presented, $x^{(i)}$ is a vector of feature values of the *ith* example in the dataset, $y^{(i)}$ is the desired output value of the *ith* example, h is the system prediction function. It's worth noting that relying solely on RMSE and MAE as indicators of forecast accuracy can be deceptive because they don't account for time series data variability (Husein and Chung, 2019).

RESULTS AND DISCUSSION

This work was implemented using MATLAB 2021a due to its ability to handle large data sets, simplicity and ease and of use. Furthermore, the platform has been the major software of choice for developing machine learning algorithms. The software ran on a Dell laptop with 16GB of RAM and running on a core i7 processor.

The forecasting results for our proposed models are summarized in Table-1. The first metric RMSE was found to be 104.34 and 110.81 for FFNN and LSTM respectively. The MAE for LSTM and FNNN was found to be 57.08 and 55.04, respectively. The results show that FNNN outperforms LSTM in terms of performance. Although the persistence model performs lower than both LSTM and FFNN, it serves as a benchmark for comparing alternative models.

Table-1 Prediction results for the Models

S/N	Performance Metric	LSTM	FNNN	Persistence Model	Units
1	RMSE	110.81	104.34	159.23	W/m²
2	Forecast Skill: RMSE	30.4	34.47	0.00	%
3	MAE	57.08	55.04	80.67	W/m²
4	Forecast Skill: MAE	29.24	31.76	0.00%	%

The result obtained in Table-1 is compared with the performance evaluation of medium-term load forecasting techniques by (Olabode *et al.*, 2020). RMSE obtained for both LSTM & FNNN are less as compared to results to a Mean Average Percentage Error (MAPE) and Root Mean Square Error (RMSE), which are 1.8212% and 0.004472 respectively. Similar results were obtained in (Guefano *et al.*, 2021). The originally measured and expected sun irradiance levels for the models FFNN, LSTM, and persistence are shown in Fig. 3. The persistence model performance was the worst in all models, as seen in the diagram. As a result, solar irradiance from the previous day has a minimal correlation with solar irradiance from the day ahead and thus is not a good predictor.

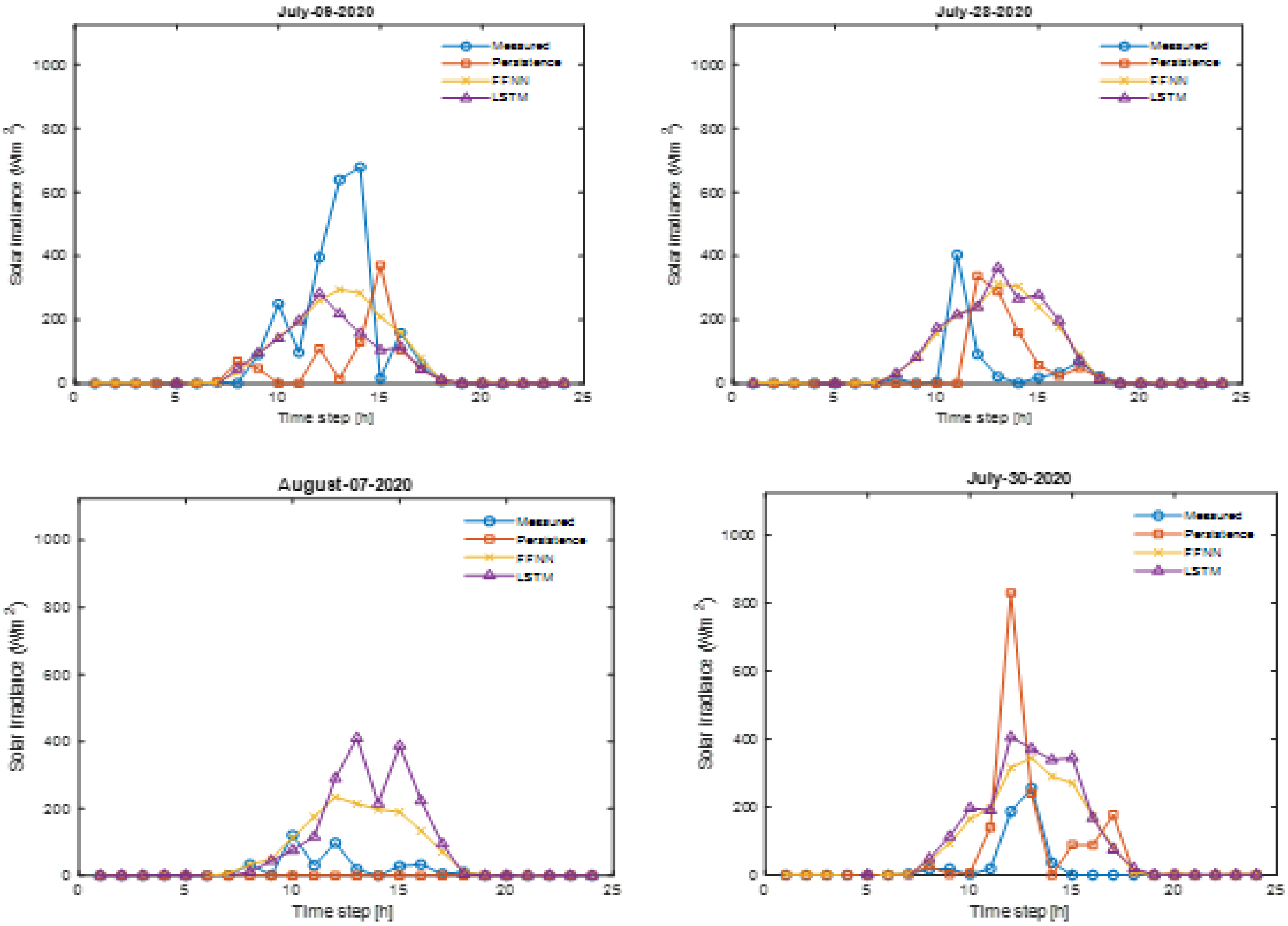

Fig. 3 Solar irradiance for LSTM, FFNN, and persistence model

The scatter plots are shown in Fig. 4. These tools are used as a visualization tool to determine the accuracy of the prediction. The measured and predicted values are plotted with solid lines indicating a near good forecast and the star indicating indicting a prediction. Therefore, marks closer to the solid lines indicate better prediction.

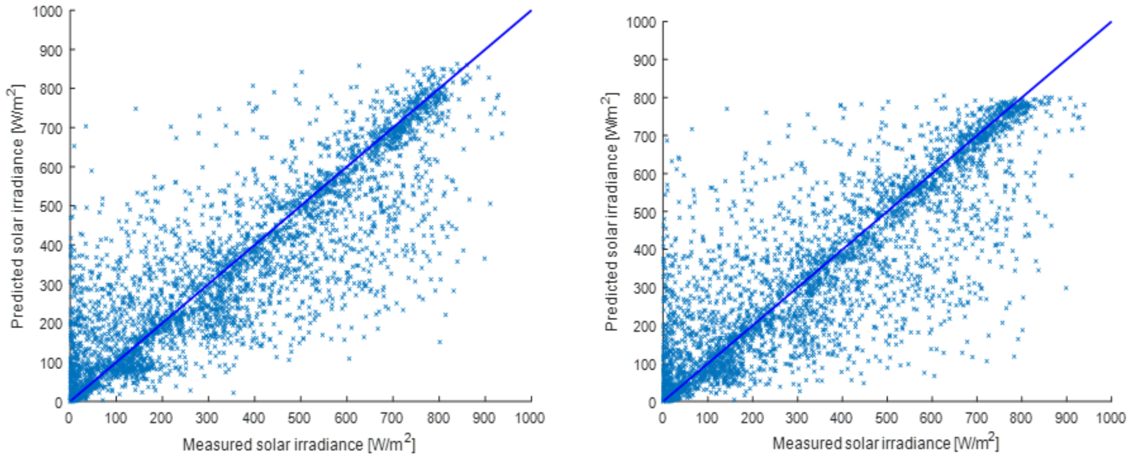

Fig. 4 Scatter plots for solar irradiance for the models.

Previous works have utilized NARX models to determine the accuracy of short-term load forecasting. Many studies find inconsistent results when evaluating the accuracy of different forecasting (Husein and Chung, 2019). They discovered that in all circumstances, no machine learning model is superior (Long, *et. al*, 2014). In addition, statistical methods are more accurate than machine learning methods in several studies (Reikard, 2009). Nonetheless, multiple studies have indicated that some models are superior to others in the literature. The disparity can be attributed to several factors, such as forecasting horizon, performance metric, input qualities, and several others. The second element is dataset variability, which affects prediction accuracy since some data are more random than others. Finally, the authors (Hand, 2006) asserted that many complex prediction systems, they argue, may be over-tuned, giving them an unjustified advantage over simpler methods in empirical comparisons.

CONTRIBUTION TO KNOWLEDGE

This study uses data from the photovoltaic geographic information system and two machine learning algorithms, the feed forward neural network (FNNN) and the long short-term memory (LSTM), to anticipate load demand in Abuja, Nigeria. To the best of our knowledge, this is the first-time data from this repository is used to perform such forecasting in the selected location using the two said algorithms. Different researchers have applied performance metrics such as MAE, RMSE and MSE. In our work, a new metric, the persistence metric was introduced to determine the robustness of the model thus providing further insight into the forecasting.

CONCLUSION

This study presents the application of machine learning approaches to short-term load forecasting of power consumption in Abuja, Nigeria. Based on data from PVGIS, two distinct models were employed to forecast load demand. Based on RMSE and MAE, it was discovered that FNNN performed better than LSTM in the two approaches used. It was observed that the RMSE of LSTM and FFNN is 110.81 and 104.34, respectively. The MAE for LSTM and FNNN was found to be 57.08 and 55.04, respectively. The persistence model consistently performs poorly in all cases, as seen in the diagram.

As a result, solar irradiance from the previous day has a minimal correlation with solar irradiance from the day ahead and thus is not a good predictor. The findings of this study may provide a solid foundation for regulators and stakeholders to make educated decisions about the region's energy consumption patterns. The results in this paper are based on a 24-hour day-ahead projection. When employing a different prediction horizon, such as that described in (Husein and Chung, 2019), FNNN may not be superior to other models. Future works would include testing the models using more data sets and incorporating more models to ascertain their accuracy.

CONFLICT OF INTEREST

There is no conflict of interest with regard to this research.

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