International Journal of Energy and Environmental Research
Vol.10, No.1, pp., 1-13, 2022
ISSN -2055-0197(Print),
ISSN 2055-0200(Online)

UNSUPERVISED DEEP ARCHITECTURE FOR FORECAST OF A TROPICAL ELECTRICITY LOAD

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Citation: Aina Segun, Adewuyi Saheed A., Amuchi David C. , and Oluwaranti Adeniran (2022) Unsupervised Deep Architecture for Forecast of a Tropical Electricity Load, *International Journal of Energy and Environmental Research*, Vol.10, No.1, pp., 1-13

ABSTRACT. *Research on electricity load forecasting has been well circulated in journals. However, this was not particularly well done in the tropics. After all, forecasting electricity loads has been established to vary along climatic regions owing to different weather conditions, with the consequential effect of contrasting load requirements. This characteristic change has triggered the purport of this study for a while. Since the study began, as this is only an extension of previously done works by this team, deep architectures have been found more reliable than the classical models for load forecasting. As a result, in this study, an unsupervised deep learning architecture namely Stacked Autoencoder (SAE) was built for and applied on a 3-year historic electricity consumption and meteorological data for day-ahead prediction of electricity consumption of a tropical region. Consequently, the developed unsupervised (SAE) model demonstrated good results on both validation and test data, and its prediction cost was very minimal.*

KEYWORDS: SAE, deep architecture, unsupervised model learning, LSTM, CNN, MLP, STLF, electricity loads forecasting.

INTRODUCTION

Electricity demand load management takes substantial effort of all stakeholders in the power sector. In order to generate, transmit and meet huge daily electricity requirements of electricity users the distribution company has huge responsibility to meet the electricity demand of its customers. Demand in this case is the consumptions on the grid which must be met and satisfactorily delivered to customers. This demand has shown significant increase with population growth [1]. Therefore, the utility company undertakes to carry out forecast of loads ahead of demand.

Load forecasting means prediction of electricity consumption on the grid ahead of actual demand. This is a typical planning technique and has implication of helping the power stakeholders to manage the power system's load effectively and efficiently. Recent market deregulation has stimulated its use especially at distribution level [2, 3, 5]. Using load forecasting approaches such as the very short-term or short-term class, the Utilities will especially make vital decisions crucial to its day to day operation. This can includes purchasing decision and power generation decision load switching, and infrastructure development, among others [2, 4, 5].

The electricity load forecasting is simplified based on the aim of the forecast that is, the values to be predicted, which can be a single value or multiple values [6]. Considering the factors affecting load consumption, which are very key ingredients for forecasting, it is important to include time, weather and class of the customer [2, 5]. These parameters will therefore include electricity load data, calendar data; or a combination of load data, calendar data and weather parameters; or another combination of load data, calendar data and other data variables which may be demographic, economic and social in nature, usually common to the modelling residential class of electricity consumption [2, 5].

Research advances have shown that aside the classical methods of forecasting electricity load; a more sophisticated approach is useable. There was issue of forecast accuracy using some of the classical machine learning techniques which deep learning method has satisfactorily demonstrated success when modeled and applied on electricity data [3]. Deep learning techniques are typical machine learning algorithms and models with ability to automatically learn tasks and features directly. Deep learning techniques will extract hidden features underlying and undermining the precision of a typical model's performance [3].

In lieu of this, this research team was concerned about exploiting this opportunity and had successfully published works in this regard. Our previous study focused on the application of a three-year load data alongside certain weather data to model some deep learning models such as the Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Multi Layer Perceptron (MLP) which are all supervised models.

In this paper, however, an unsupervised deep learning model, Stacked Auto Encoder (SAE) was adopted and developed for the same problem. The data is based on three-year historic electricity loads collected from the Transmission Company of Nigeria (TCN) and one year weather data collected from the Nigerian Meteorological Agency (NiMet) for an institutional customers [3]. The datasets are preprocessed for various anomalies, such as inputting the missing values and the models are applied to the datasets with the results being analysed for their training, validation and prediction scores. The eventual outcome shown tremendous improvement on the previous output from our studies which suggests that unsupervised model such as SAE is more reliable than the supervised LSTM, CNN and MLP models that were used in modelling forecast of electricity consumption especially in the tropics.

RELATED WORK

The last few years have seen many works done in this research domain by application of deep architectures in solving the power sector vast problems particularly on modeling electricity consumptions prior to their actual demands, which in essence is the purport of this paper. For instance, a Short Term Load Forecasting (STLF) solution was developed using Deep Neural Network (DNN) approach and the authors worked by comparing DNN with other traditional methods including regression trees, moving averages, and support vector regression. The approach adopted was either with or without DNN pretraining [7]. Essentially, the DNN implemented with pretraining was achieved by doing so using the Stacked Autoencoders (SAE), standard Recurrent Neural Network (RNN) and hybridized RRN-LSTM deep architectures. Consequently, the authors reported that, in all the DNN models and the baseline techniques, the pretrained-DNN using SAE resulted as the most promising and the most stable in terms of behavior especially at 200 and 400 epochs of data exposures during experimentation or model training [7]. Similarly, in another study which proposed stacked autoencoders (SAEs) with Extreme Learning Machine (ELM) for prediction of building energy consumption. The SAEs were particularly

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adopted in order to extract a building energy consumption features and the ELM was the predictor. The authors claim that the outcome of the proposed approach outperformed (in every sense) all other candidate machine leaning techniques namely the support vector regression, multiple linear regression, backward propagation neural network, and the generalized radial basis function neural network, upon comparison [8]. In [4], a time-wise STLF system was proposed. The work carried out performance comparison on two DNNs, the feed-forward DNN and recurrent DNN models based on their computational performance and accuracy. The work introduced the utilization of time-frequency feature selection procedure, initiated by the two models, which further reveals the hidden dominant factors that are very responsible for electricity consumption. So, data analysis was based on the two domains, time and frequency domains, which was done systematically and in succession as the frequency domain components are transformed back to the time domain resulting in capturing of the latent features in the dataset which are essential for modeling accurate day-ahead load estimation [2]. Furthermore, adoption of the SAE and the Gated Recurrent Unit (GRU) neural network was reported for development of a STLF problem [9]. This approach utilized datasets comprising historic electricity consumption, weather parameters, and some holiday data [2, 5]. The method specifically utilized autoencoding for compression of the historical data and the multi-layer GRU for constructing the predictive model. The work also reports that the proposed approach has capability to effectively predict loads with lower prediction error and higher precision. In terms of performance evaluation, it was found to be more advantageous when compared to another a DNN such as the LSTM and a classical neural network namely Support Vector Machine.

Summarily, the foregoing review has clearly intimated previous work in this problem area particularly on relevance and use of the SAE deep architecture in relation to modeling of electricity consumptions for STLF. All of the reported works either used the SAE deep architecture as a pretraining model or for data exploitation. Similarly, another study also reported that the autoencoder, which is a single form of the SAE, as a means of data encoding [9]. Conversely, in this paper we present a STLF problem for a tropical region. The study is a conclusive position of our previously published paper [3] which developed a deep learning model for electricity demand forecasting using the MLP, CNN and LSTM models. Moreover, in this work we rather adopt use of SAE deep architecture for the same problem.

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METHODOLOGY

In this section we present the information about the nature of the data used for this work. This covers source of the dataset, data preprocessing, and data splitting. Following this, we briefly introduced the SAE architecture. Consequently, the predictive model for the problem is presented alongside the performance evaluation metrics. For clarity purposes, Fig. 1 shows the systems design architecture and processes involved.

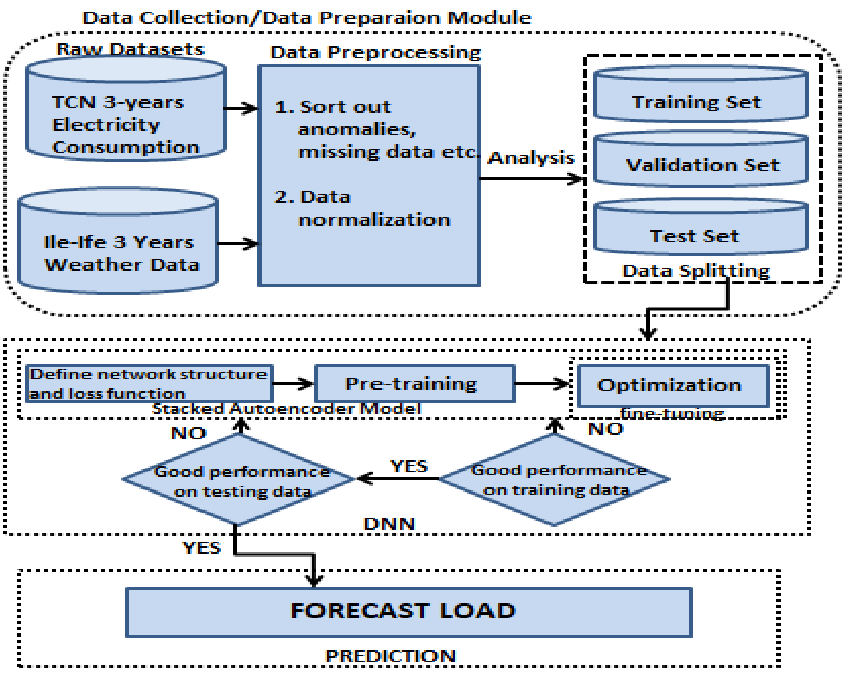

Fig.1. The electricity load forecasting model system architecture.

Data Collection and Preparation

The electricity load forecasting data was sourced from the national power carriers both at the Transmission Company of Nigeria (TCN), 132/33kV substation, Ajebandele, Ile Ife and the National Control Centre (NCC), Osogbo covering three years. Similarly, we sourced for weather data at the Nigerian Meteorological Agency (NiMet), IdoOsun for the study area, Obafemi Awolowo University (OAU) covering the same period. The electricity load data which is the main dataset is characterized by *"date," "time," "datetime"* and *"load"* features and the corresponding weather dataset has only three features namely *"wetblb," "dryblb,"* and *"rh."* For illustration purposes, Fig. 2 shows a visual representation of the two datasets done using the *Matplotlib* module in *Python 3*.

The raw dataset with features stated above do not properly accentuate various factors responsible for load profile and its model outcome turns out in highly statistically non-linear and complex consumption profiles. Conversely, when the same datasets were further processed such that its hidden features were revealed, we had the following added features: *previous one hour*, the *previous two hours*, the *previous day same hour*, the *previous day past hour*, the *previous day past two hours*, the *past two days same hour*, the *past two days previous hour*, the *past two days previous two hours*, the *past week same hour*, the *average of the last 24 hours*, the *average of the past seven days*, *days of the week*, *weekend*, and *holiday*. This was only possible after critical study of the datasets, which consequently inspired the need for the introduction of calendar features as complexities to the raw electricity load datasets in order to bring out the best out of it as indicated in Table 1.

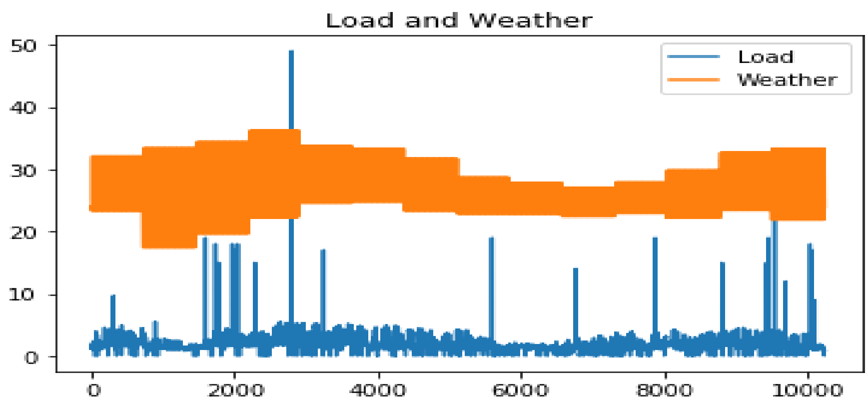

Fig. 2. Graphical view of the model's datasets.

Further to this, based on domain knowledge, power data are a time-series and can therefore possess some defective entries whose presence may deteriorate the quality and performance of the proposed model. Therefore, defective data such as missing values and loads with zero values were cleansed and sorted for noise and inconsistencies. Preparing data for the proposed SAE model requires that it be preprocessed by scaling numeric data and transforming categorical data. Data scaling was applied to numeric

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data input for model training to improve network stability and modeling performance. Therefore, data standardization method was adopted thus numeric data were scaled and categorical data were transformed. The eventual dataset consists of 10,246 samples with 21 features. The data was consequently split into training, validation, and test sets of size 68%, 15%, 17% respectively as shown in Table 2.

Stacked Autoencoder Deep Architecture

The Stacked Autoencoder (SAE) is designed to employ multiple autoencoders in the building blocks of deep architecture [8, 10]. The SAE architecture has an autoencoder in each layer [7] and this autoencoder is a neural network that has capacity to encode its input data into a new form using unsupervised learning. These are hidden layers of neurons trained to encode raw input data features into a new form and decode same for reconstruction of original data input with very minimal deformation [3]. A typical structure of autoencoder is shown in Fig. 3 and its details are already published in [2].

Table 1. Detailed description of the model feature

SN	LABEL	LABEL MEANING	DESCPTION
1	Date	Date	Date load was recorded.
2	Time	Time	Time load was recorded.
3	DateTime	DateTime	Date and time load was recorded in a day.
4	Load	Power demand	Load recorded at every one hour of a day.
5	P1Hr	Previous 1 hour	Load recorded at an hour before the current time.
6	P2Hr	Previous 2 hours	Load recorded at 2 hours before the current time.
7	PDSHr	Previous day same hour	Load recorded at the same hour of a previous day.
8	PDPHr	Previous day previous hour	Load recorded on previous day at previous hour before the current time.
9	PDP2Hr	Previous day previous 2 hours	Load recorded on previous day at previous 2 hours before the current time.
10	P2DSHr	Previous 2 days same hour	Load recorded on previous 2 days at the same hour of the current time.
11	P2DPHr	Previous 2 days previous hour	Load recorded on previous 2 days at previous hour before the current time.
12	P2DP2Hr	Previous 2 days previous 2 hours	Load recorded on previous 2 days at previous 2 hours before the current time.
13	PWSHr	Previous week same hour	Load recorded on previous week at the same hour of the current time.
14	AvePast24Hr	Average of past 24 hours	Average loads recorded on past 24 hours of the current time.
15	AvePast7D	Average of past 7 days	Average loads recorded on past one week of the current time.
16	DayWeek	Day of the week	Day type of the week.
17	isWeekend?	Weekend	Weekend data.
18	isHoliday?	Holiday	Holidays loads including public and sessional breaks.
19	RH	Relative humidity	Weather parameter for determining amount of water vapour in air.
20	DRYBLB	Dry bulb	Weather parameter for determining air temperature.
21	WETBLB	Wet bulb	Weather parameter for determining air moisture temperature.

Table 2. Number of instances

	Training Data	Validation Data	Test Data
No of instances	6968	1536	1742
Proportion	68%	15%	17%

Performance Evaluation Metrics
In this paper, since it is a regression problem, linear regression objective function was adopted for the estimation of cost of prediction. So, we adopted the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) for SAE training performance.

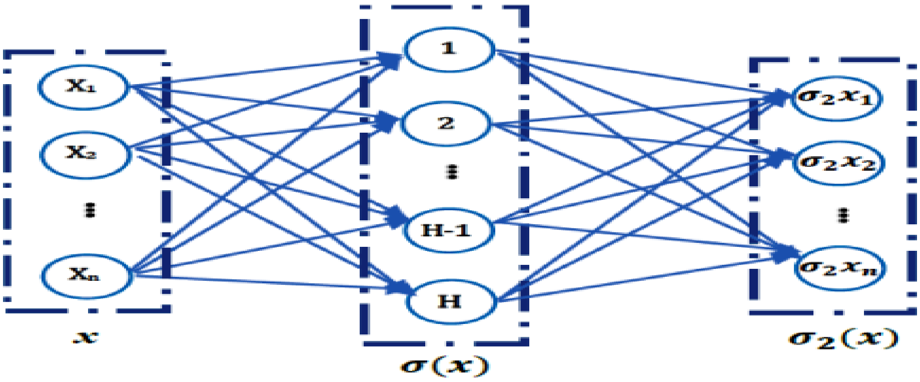

Fig. 3. A simple structure of an autoencoder [2].

1. Implementation and Result

1.1. Training Performance

Evaluation of the performance of the model during training was carried out using the mean absolute percentage error and mean absolute error.

Mean Absolute Error (MAE). The MAE is defined as:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|Y_{pred} - Y_{true}\right| \quad (1)$$

Mean Absolute Percentage Error (MAPE). The MAPE expresses prediction accuracy in terms of percentage and is defined by the relation:

$$\mathrm{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{Y_{true} - Y_{pred}}{Y_{true}}\right| \quad (2)$$

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Root Mean Square Error (RMSE). The RMSE is the standard deviation of the prediction error, which is the distance between the regression lines and data points. Formally, the RMSE is given as below:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{pred} - Y_{true})^2} \quad \textbf{(3)}$$

Where, N is the number of observations, Y_{true} and Y_{pred} is ordinates of the actual and predicted loads respectively.

Fig. 4 and 5 are visual descriptions of the SAE model's performance during training at 100 epochs of data exposure. We used linear model module imported from the *sklearn* library to calculate these metrics and *mathplotlib* package was employed to generate the visual descriptions. From the result these processes, the SAE model progressively minimized the prediction cost.

SAE Model Learning Loss

The SAE model networks performance was evaluated on the test dataset so as to know the capability of it in making predictions especially with unseen data. The model performance is satisfactory via all test patterns and the evaluation metrics. The visual outcome of this event is reported in Fig. 6.

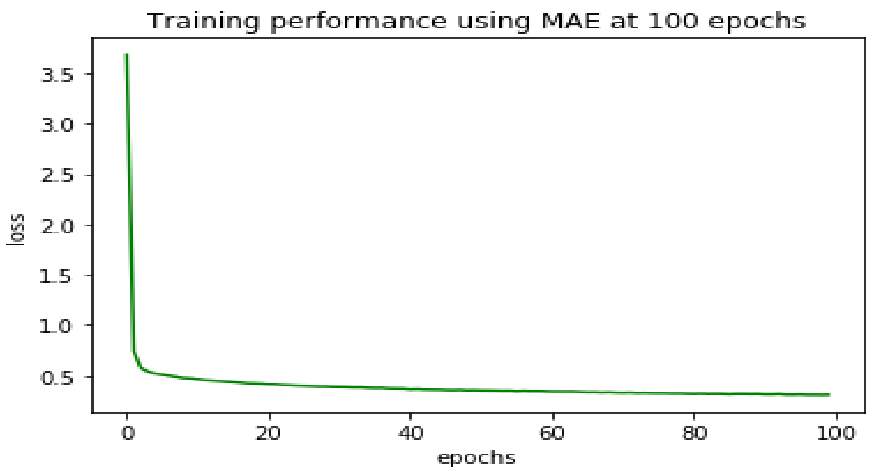

Fig. 4. Proposed SAE model performance evaluation during training.

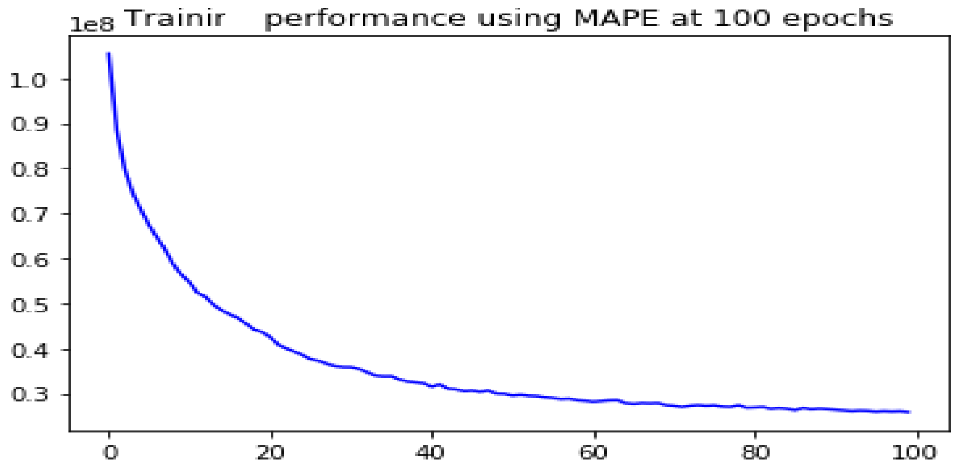

Fig. 5. Another SAE model performance evaluation during training.

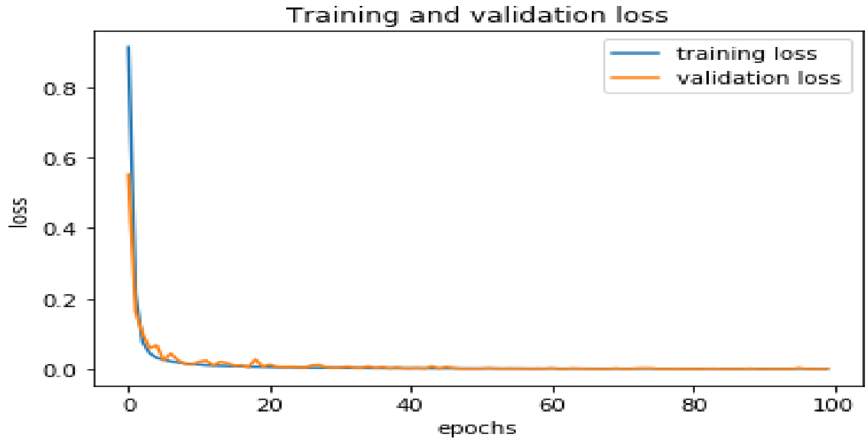

Fig. 6. The SAE model learning loss at 100 epochs.

Experimental Outcome

Fig. 7 presents the actual electric-power load consumption and the predicted outcome based on the test data. Evidently, the predicted outcome is close to the actual throughout. The graph is a prediction outcome of the SAE model for the next day loads, done at 100 epochs in line with the experimental approach adopted for the implementation. The walk-through the predictions from epoch to epochs significantly shown positive progression in the ability of the SAE model as an accurate technique for modeling electricity consumption. The initial error training is lesser because of the unsupervised layer-wise pretrained step in the SAE architecture which initializes parameters. This is also the reason for the model to reach convergence point faster.

The prediction scores or outcomes of evaluating the SAE networks revealed that at epoch 100, the performance of the model was appropriate and did not underfit nor overfit, which makes it a good point for the model.

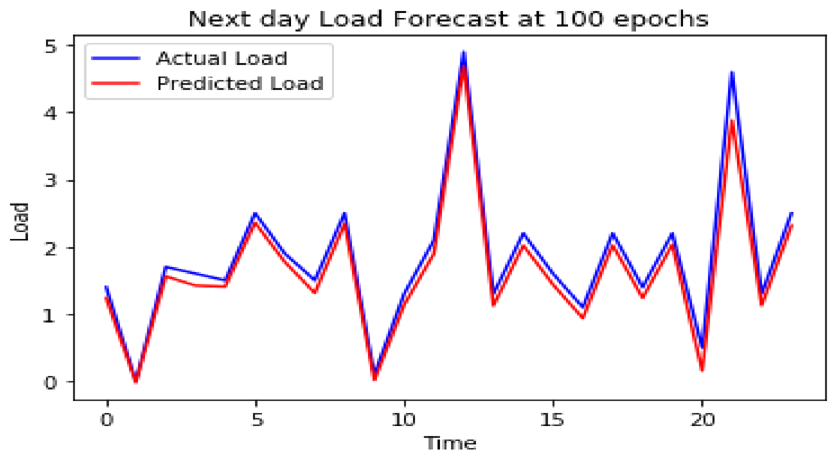

Fig. 7. Forecast of actual load versus predicted loads at 100 epochs for the next day.

However, at 200 epochs it signals a situation that suggested ending the experiments so as to avoid overfitting the networks. This suspicion was subsequently confirmed at 300 epochs. Table 3 shows the SAE model performance at 100, 200, and 300 epochs with respective RMSE, MAE and MSE performances on validation / test sets. This result clearly depicts that as the model learns, the network optimizes itself to achieve the aim of the objective function, which is to minimize error.

Table 3. SAE performances at different experimentation levels.

Metrics	**100 epochs**	**200 epochs**	**300 epochs**
MAE	0.1693	0.0455	0.0220
MSE	0.0421	0.0024	0.0024
RMSE	0.2052	0.0492	0.0496

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CONCLUSION

The outcome of this paper has further demonstrated efficacy of deep learning approach to electricity load forecasting. Interestingly, from all the four deep learning architectures learned so far on this foreclosing project, the SAE model has proved most worthy for deployment for the Utilities in the tropics. Its outcome is the best of MLP, CNN and LSTM, which were previously studied. This in essence validates the purport of this long investigation and has equally shown that our choice of datasets is very reliable for modeling near-precise electricity demand forecasting. The implication of this will therefore be for the distribution company to plan well and ensure that power supply gets to its customers adequately. Moreover, day-ahead market entry will be a lot precise and devoid of speculations.

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