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Case Study

Enhancing Energy Demand Prediction Using Elman Neural Network and Support Vector Machine Model: A Case Study in Lagos State, Nigeria

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Abstract: Energy and power resources must be managed well to guarantee their best use. To ensure that the required demand for energy generation is met, it is necessary to estimate Energy Demand (ED) accurately. Regression analysis and time series analysis were the mainstays of ED prediction in the past. But thanks to recent developments, accuracy has been increased by utilizing machine learning (ML) techniques to identify trends in data on electricity consumption. The purpose of this study is to offer insightful information on the relationships between various variables and how those relationships affect trends in energy usage. The goal is to create a prediction model that can reliably predict ED in a certain study area. In Lagos State, Nigeria, the Elman neural network (ELNN) and support vector machine (SVM) model are used for ED forecasting. The performance of SVM is optimized by selecting suitable kernel functions. The research region's 24-hour dataset was used to train the SVM model. Metrics including the correlation coefficient (R), Pearson correlation coefficient (PCC), mean square error (MSE), mean absolute error (MAE), and Root mean square error (RMSE) were used to evaluate the ML model. The findings show that the ELNN-M3 model fits the data well (R > 0.9). It is noteworthy that the study considered temperature, wind speed, and sun radiation as predicting variables. This study adds to the ongoing attempts to improve the accuracy of energy demand prediction, especially in dynamic contexts such as Lagos State.

***Keywords*:** prediction, support vector machine, artificial intelligence, energy demand, machine learning

1. Introduction

Due to advances and the increasing awareness of renewable energy (RE) production all over the world, RE market sources have been escalating. The sources of RE are estimated to outperform fossil fuels in monthly generation [1]. However, up-to-date kinds of literature curtained that electrical needs always arise from difficult interactions between

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personal and socio-economic factors, all these mentioned sources make it difficult when it comes to energy demand (ED) valuation. Thus, the appropriate model that could make an accurate ED assessment would need to access a virtually infinite data source to feed the model with the latest information. In both situations, the lack of data and link to computational problems means that many researchers are ineffective in examining foreseeable models with fractional information within this framework. The power consumption guess has been attempted from different perspectives. For the variation of wind power and solar radiation, it is very often difficult to make accurate predictions of ED [2]. Accordingly, the management of power sources and electricity needs to be well managed to ascertain the efficient usage of electricity. High capacity planning, scheduling, and operation of electric power (EP) systems are surely in need. EP, consumption, and distribution mostly take place at once, which demands the requirement for precise electrical petition approximation to make sure that the electricity cohort is efficient enough to meet the need.

Energy demand faces numerous challenges, together with the want for reliable and sustainable strength assets to satisfy growing consumption, mainly in urban areas. The fluctuating availability of renewable energy because of weather situations creates instability in delivery, necessitating advancements in energy storage technology. Additionally, balancing energy efficiency with monetary increase is critical, as developing areas are trying to industrialize without exacerbating environmental troubles. Infrastructure limitations, regulatory hurdles, and the want for considerable investment in modernizing the grid similarly complicate the panorama. Lastly, the transition from fossil fuels to purifier options poses technological and coverage-driven challenges, requiring coordinated efforts throughout more than one sector.

Managing Energy Demand poses a complex challenge that is deeply rooted in the intricate interaction of multiple factors. Essentially, the challenge revolves around the accurate prediction and fulfilment of the varying demands for electricity and power across different temporal and spatial scales. Factors like population growth, industrial development, technological progress, and changing consumer trends contribute to the intricate nature of this situation. The task of balancing these dynamic factors necessitates advanced techniques for Energy Demand (ED) estimation that surpass conventional approaches. The incorporation of machine learning (ML) and sophisticated data analytics has emerged as a promising strategy to tackle these complexities, facilitating more accurate forecasting and proactive management of energy resources. Obstacles persist with respect to the precision of data, the capacity for expansion of models, and the necessity for flexible approaches to address the changing trends in energy consumption and environmental concerns. Addressing the challenge of Energy Demand effectively necessitates a holistic strategy that combines technological progress, policy structures, and cooperation among stakeholders to build enduring and resilient energy systems for the future.

However, Predicting ED is difficult as demand series can come with unexpected developments, noise levels, and exogenous variables. Even though there is a strive for smearing DE, the need for a power projection pact has been a hotly debated topic in recent years [3]. The estimation of electricity load (EL) is paramount for power system grounding espoused by energy benefactors. Even a small advancement in EL prediction could lessen cost and advance in trading merits, more especially during a time of electricity peak ingestion time. Yet, it's principal for those in charge of providing the electricity to model and predict load as precisely as they can for both short-term and medium-term periods. With an estimated population of almost 190 million, Nigeria has a peak energy demand of over 17,700 MW in 2017 the nation detailed an all-time peak electricity generation of 5,074 MW spawned with 29 grid-link power plants. Nigeria's national electrification rate is only 58% with a substantial disparity between urban areas 79% and rural areas 39%. Grid advancing to local places is rear by poor ways connectivity, rough terrain, dense jungle, and poor energy usage. In the upbringing situation concerns over climate change, the Nigerian electrical power supply industries are assisting to depend on RE ways for electricity generation which include biomass, geothermal, solar, and wind. All these mentioned have the merit of being free, eco-friendly, and are inexhaustible sources [4].

With the advances in AI and ML technology, new methods have been used for prediction in power companies, where massive electricity data need to be managed precisely [4-13]. AI could be used in the electricity industry (EI) for power demand (PD) and supply assessment [14]. The AI model factors are predicted using statistical methods on historical data of loads and some aspects affecting it. The methods used for parametric ED can be classified into three methods. Regression, time series, and prediction techniques [15] perceived that AI and ML-based electricity estimation ways have precisely given excellent estimation than other conventional techniques and linear and nonlinear regression.

In response to the experiment on energy demand, Kim et al. [16] employed a based transfer learning model to advance the estimation presentation of building energy end-use and the validation techniques for target work values. The long short-term memory (LSTM) based on simulated data in the base domain was used to transfer to the target domain with insufficient data from the limited simulation data. Rao et al. named cluster microgrids, which helps to reduce the utility grid burden. However, these cluster microgrids require a precise electric load projection to manage the operations, as the integrated operation of multiple microgrids leads to dynamic load demand. Thus, load forecasting is a complicated operation that requires more than statistical methods. There are different machine learning methods available in the literature that are applied to single microgrid cases. In this line, the cluster microgrids concept is a new application, which is very limitedly discussed in the literature. Thus, to identify the best load forecasting method in cluster microgrids, this article implements a variety of machine learning algorithms, including linear regression (quadratic [17] employed different machine learning models including linear regression (LR), support vector machines (SVM), LSTM, and artificial neural network (ANN) to predict load demand. The efficiency and effectiveness of the employed model are examined using three performance metrics (RMSE, MAE, and R2), the outcomes depict that, ANN surpasses the LR, SVM, and LSTM in terms of accuracy and effectiveness during the modelling phase. In an island region study, Karacostas et al. [18] employed the ANN model to predict ED, which concerns 24 hours ahead on an hourly basis. In the study, the ANN model was fed with historical data of ED, which used a biometeorological index known as the cooling power index. The results indicate that the models come out with excellent results. From Wuxi City, eastern China, Yin et al. secondary, and tertiary industry gross domestic product (GDP [19] employed ANN and multilinear regression (MLR) in other to estimate the ED. The models were trained and validated using historical data from 1991 to 2016. During the modelling phase, the result shows that ANN has less amount of error of 1.58% compared to MLR (2.71%), where ANN outperformed MLR which attained an excellent result. In the Cloudera cluster study, Cáceres and Merino [20] employed a random forest (RF) algorithm within a massive data environment to propose the household ED valuation. The assessment is based on the use of information from many ways affirming a groundbreaking role of socio-economic data in consumers' attitudes.

Based on the recent works of literature, AI-based methods entailing ANN and GPR become the most paramount ways for ED prediction with the best performance of any other techniques. The review in this study shows that many ED predictions. Replicas have been developed for the estimation of ED at grid and national levels. Furthermore, there have been a few kinds of literature works on ED prediction at minor levels including micro-grids, commercial areas, and industrial units as well as households. This paper uses the account of several analyst variables (wind speed, temperature, and solar radiation) for advanced prediction and accuracy of the model. Besides, SVM is employed in this study for the ED prediction. This study significantly advances energy management and forecasting by enhancing the accuracy of energy demand (ED) estimation, crucial for optimizing energy and power resource utilization. Transitioning from traditional regression and time series analysis to advanced ML techniques marks a pivotal shift, ensuring that energy generation meets demand effectively. The study focuses on understanding complex variable relationships and their impact on energy consumption trends, and demonstrates the practical utility of proactive energy planning using a customized forecasting model in Lagos State, Nigeria as an example. The enhancement of the Elman neural network (ELNN) and support vector machine (SVM) model through suitable kernel functions highlights their dependability in predicting ED. This assertion is substantiated by strong performance metrics such as the correlation coefficient (R), Pearson correlation coefficient (PCC), mean square error (MSE), and root mean square error (RMSE). The ELNN-M3 model illustrates a notable concordance with the dataset, as indicated by a value of R greater than 0.9. Incorporating critical variables like temperature, wind speed, and solar radiation enriches the study's relevance, contributing significantly to ongoing efforts in improving energy demand prediction accuracy, particularly in dynamic contexts, and supporting sustainable energy management and resource planning endeavors.

2. Proposed methodology

In this study, we combined two machine learning models, the Elman Neural Network (ELNN) and the Support Vector Machine (SVM), to enhance energy demand forecasting (Figure 1). We selected Lagos State, one of Nigeria's prominent cities, as a representative case study. The dataset collected from this study area holds significant importance. However, the advancement of the machine learning models was divided into two steps, to which 30% testing and the remaining 70% for training. Additionally, the data was collected, tested, coded, and looked over before the data processing took place to the range of the best model of the fit. For this study, the load demand (LD) data was outlined from a remote block of a flat house that contained at least 10 apartments, and it was targeted via survey. Also, the number of electrical appliances where regarded according to their time of usage for all 10 apartments. The hourly data were calculated using physical faltering and a record of an hourly variation of the clear load in 24-hour windows. Therefore, this study employed a Support vector machine (SVM) in other to predict the ED in the Lagos case study. The study input variable includes wind speed (WS), Solar radiation (SR), Temperature (T), and Energy demand (ED) as the output variable.

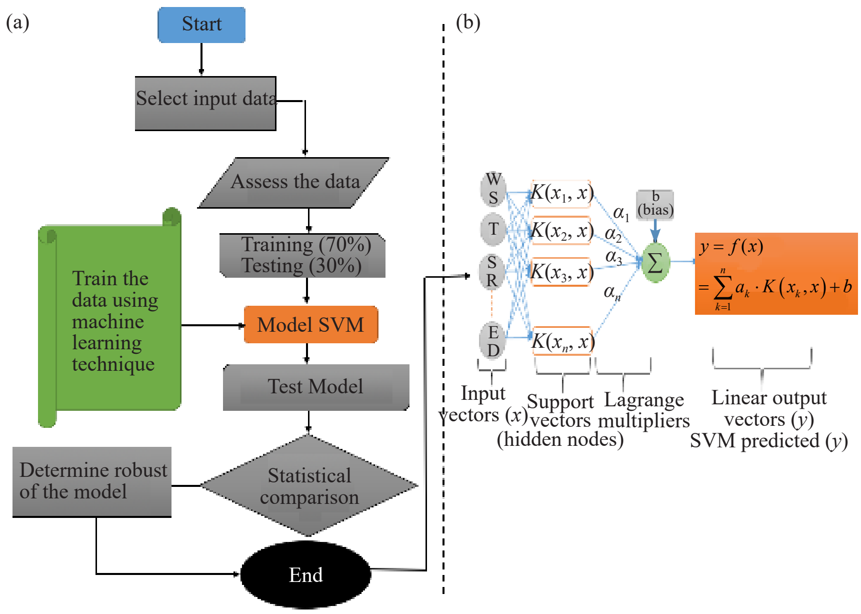

Figure 1. (a) Proposed model improvement flowchart for the study; (b) the structure of the proposed SVM

2.1 *Study area*

Lagos State is among the most populated states in Nigeria, and it's a coastal region with its capital in Ikeja. The region is located in the southern of the country and is almost the commercial center of Nigeria. However, Lagos State is estimated to be the biggest city in Africa in 2020 with a growth in population of almost 8% per year and an immigration rate of about 9% a higher population rate in the metropolitan area [21].

2.2 *Elman neural network (ELNN)*

In 1990, Elman presented the Elman neural network. Based on the basic architecture of BPNN, it is a kind of recurrent neural network with many connected neurons [22]. To perform memory, an additional extension layer is added to the hidden layer and functions as a one-step delay operator. Most frequent network topologies are one of three types: feed-forward neural networks, feed-forward feedback neural networks, or self-organizing neural networks [23]. These types of networks are based on the connections between neurons in a network. Information is simultaneously transmitted in both forward and reverse directions by the feedback network. Neurons in one layer or numerous network layers may be involved in the feedback from this data. A popular multi-layer feed-forward neural network with strong nonlinear mapping capabilities and outstanding generalization capabilities is the Back-propagation Neural Network (BPNN) [24]. The weight in the network is affected by both the forward propagation of information and the back propagation of mistakes during training. To guarantee that the Back-propagation (BP) neural network's predicted output consistently approaches, the expected output, the value, and threshold are adjusted. Typically, the Elman network model's hierarchical model has four layers [25-26]: The signal is transmitted to the hidden layer by an input layer consisting primarily of linear neurons, where an activation function is used to translate or expand the signal. The context layer is the following layer, and it can remember the previous instant values of the output of the hidden layer and can operate as a one-step delay operator. This layer also has a feedback feature. The results are finally output via the output layer [27-29]. The structure of ELNN is shown in Figure 2.

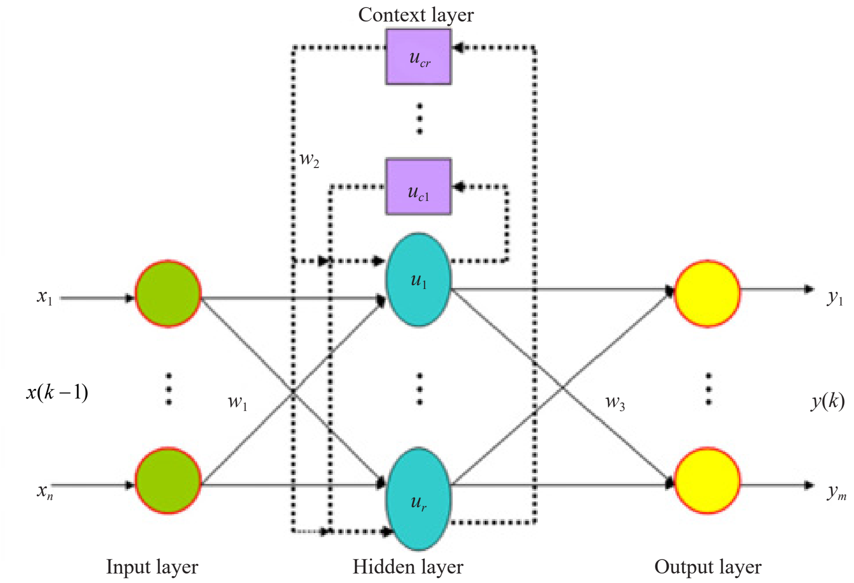

Figure 2. Structure of Elman neural network (ELNN)

2.3 *Support vector machine (SVM)*

SVM has become one of the most widely used arithmetical erudition performances in 1995 [30]. The capability of SVM to form excellent simplification makes it widely used in literature. The tendency to overfit the input data is low. SVM consents for concurrent error minimization using a kernel function to make original inputs separable in a plotted high intergalactic feature dimensional [31]. Support vector machine estimate function is considered as one of the prominent outline techniques [30]. While inserting the kernel function, SVM adds a powerful method suitable for regression exploration. SVM was firstly employed as the offered classification routine and afterwards adopted as a regression method. The methods employed in SVM to organize dribble number of research have been used for the estimation of nonlinear models. For nonlinearity in the scheme [32], the ability to perform SVM has been used for claims in several fields of science. SVM brought changes in an ancestry year in the features of model changes used for classification and regression problems. SVM becomes forward-thinking in learning models and statistics, from risk hypothesis minimization and the sureness intermission of the ML to triumph proficiency of excellent generalization. SVM is measured in different forms which are merged with estimation enquiry and the support vector classification (SVC) that deals with classification issues. It can be denoted as [33]:

$$f(x) = w \cdot \phi(x) + b \tag{1}$$

Where w represents the weight of the vector highlight in the feature space, ϕ is donated as the transfer function and b is reflected as the bias. To represent the (SVM) function $f(x)$, the matter of regression can be described as:

$$\text{Minimize } \frac{1}{2}\| w \|^2 + c\sum_{i=1}^{N}(\xi_i + \xi_i^*) \tag{2}$$

$$\text{Subject to the condition}\begin{Bmatrix} y_i - f(x) \le \varepsilon + \xi_i \\ f(x) - y_i \le \varepsilon + \xi_i^* \\ \xi_i,\ \xi_i^* \ge 0,\ i = 1,\ 2,\ 3,\ \ldots,\ N \end{Bmatrix} \tag{3}$$

Where c is the regularized constant, and ξ_i and ξ_i* are two slack variables. By managing the librarian functions, the solution of the non-linear regression function can be given based on the optimization below:

$$f(x) = \sum_{i=1}^{N} (a_i - a_i^*) K(x,\ x_i) + b \tag{4}$$

Where $K(x, x_i)$ is the kernel function, and a_i and a_i* are pair variables, both greater than 0. There are different kernel functions, such as polynomial sigmoid, linear, and radial basis function between the kernel utilities. The most known kernel recycled in the literature is the RBF kernel, hence the RBF kernel was espoused in this study. The RBF kernel used here is defined by

$$k(x,\ x_i) = \exp(-y\| x_i - x\|^2) \tag{5}$$

Where y is the kernel parameter; SVM recital is influenced by three parameters, c, y, and $\mathcal{E}$; A detailed report of SVR is available.

2.4 *Model validation*

A predetermined set of criteria and measurements has been used to evaluate each predictive performance's efficacy, efficiency, and quality. They offer a foundation for assessing performance and helping decision-makers make well-informed choices on awards, promotions, or performance enhancements. Five statistical metrics were used in this study to evaluate the models' accuracy: mean square error (MSE), mean absolute error (MAE), Root mean square error (RMSE), Pearson correlation coefficient (PCC), and correlation coefficient (R). Table 1 displays the formal ranges of the performance criteria, which are widely employed in research to evaluate the expected model's performance.

Where $ED_{(p)}$ and $\widehat{ED}_P$. indicate the predicted ED and $\widetilde{ED}_P$, the predicted mean ED, $ED_{(o)}$ observed ED, $ED^i_{(o)}$, $\overline{ED_{om}}$ indicates the observed mean ED, and N indicates the number of the data set.

Table 1. Performance evaluation

Name	Formula	Range
PCC	$PCC = \dfrac{\sum(ED_0 - ED_{om})(ED_p - ED_{pm})}{\sqrt{(ED_p - ED_{pm})^2 - (ED_0 - ED_{0m})^2}}$	$(-\infty < NSE < 1)$
R	$R = \dfrac{\sum_{i=1}^{N}\left[ED_O - \overline{ED_{om}}\right]\left[\widehat{ED}_{P.} - \widetilde{ED}_P\right]}{\sqrt{\sum_{i=1}^{N}\left[ED_{(P)} - ED_O\right]^2\left[\widehat{ED}_P - \widetilde{ED}_O\right]^2}}$	$(-1 < R < 1)$
MSE	$\dfrac{MSE = \left(\sum_{i=1}^{N} ED_{(p)} - ED_{(o)}\right)^2}{N}$	$(0 < MSE < \infty)$
MAE	$MAE = \dfrac{\sum_{i=1}^{N}\lvert ED_{(p)} - ED_{(o)}\rvert}{N}$	$(0 < MAE < \infty)$
RMSE	$RMSE = \sqrt{\dfrac{\left(\sum_{i=1}^{N} ED_{(p)} - ED_{(o)}\right)^2}{N}}$	$(0 < RMSE < \infty)$

3. Result and discussion

This section examines the data source's pre-processing, model building, and computational results. Energy demand (ED) is compared to other components using ELNN and SVM models. The MATLAB R2023a toolset was used to generate the machine learning models (ELNN and SVM), and E-Views 13.0 was used to pre-process and post-process the data. MATLAB code was utilized for both the training and validation of the model for ELNN and GPR. Choosing the right model structure is essential to achieving successful generalization. In order to overcome hypersensitivity, methods including adjusting the maximum number of iterations (1,000), learning rate (0.01), and MSE (0.0001) were used with the ELNN. The layers are found by using the formula $(2\sqrt{n} + m)$ to $(2n + 1)$, where n is the number of input neurons and m is the number of output nodes. Determining the appropriate number of hidden nodes is a crucial step in building an ELNN. The dataset was divided into folds in order to prevent over fitting. The performance of each fold was evaluated, and SVM was used with a 5-fold cross-validation. The relationships between ED constraints in a complex system could not be linear because of the volatile nature caused by several factors. The correlation matrix, represented by Figure 3, shows the relationship between the independent and dependent variables.

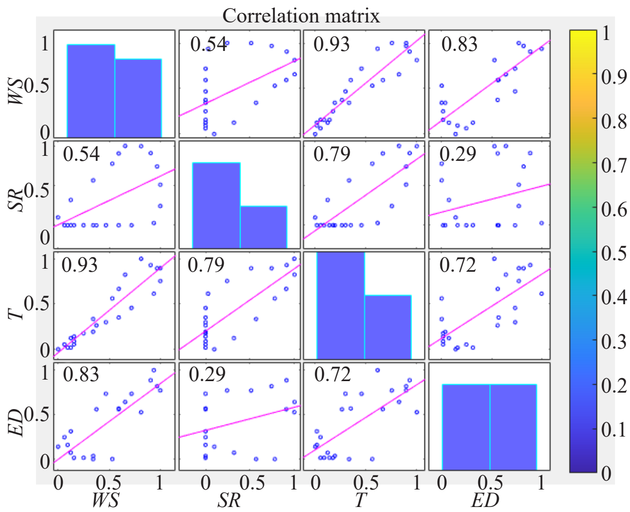

Figure 3. Correlation matrix (relationship between dependent and independent variables)

Table 2 offers statistical summaries of the datasets and key data required for model development to concisely communicate the essential features of the datasets, compare variables or groups, spot anomalies, preserve data accuracy, and aid in decision-making processes. This table make it easier to explore data and help analysts and researchers draw meaningful conclusions from the data.

Table 2. Descriptive statistics of the input and output variables

Variable	*WS*	*SR*	*T*	*ED*
Mean	2.716667	229.7917	26.80417	20,197.08
Kurtosis	-1.3620	-1.0073	-1.3028	-1.5928
Skewness	0.2802	0.8535	0.4547	0.1553
Minimum	1.2	0	24.5	3,480
Maximum	4.4	777	30.2	45,275

In addition, the dataset was normalized using equation 6 as shown below in order to reduce data redundancy and improve data integrity after a thorough study of the data.

$$X_i = \frac{x_{initial} - x_{\min}}{x_{\max} - x_{\min}} \tag{6}$$

The data to be normalized is represented by x_{initial}, the minimum and maximum values within the variable range are represented by $x_{\min}$ and $x_{\max}$, and the normalized data is represented by X_i.

By using sensitivity analysis and CC, the combination of input features generated by evaluating Eq. (7) will be used as inputs for modelling the ELNN and SVM models.

$$ED = \begin{array}{l} M1 = WS \\ M2 = WS + T \\ M3 = WS + T + SR \end{array} \tag{7}$$

Where WS stands for wind speed (m/s), T indicates Temperature (°C), and SR means Solar Radiation (W/m^2).

3.1 *Result of the machine learning*

From the table below, it can be seen that, during the modelling of ELNN, the highest accuracy was achieved by the model combination M3 in both calibration and verification phase, with PCC and R equal to 0.9570 and 0.9596 and the minimum error of MSE = 0.0089. While during the modelling of SVM, the highest accuracy was found to be at model combination M3 in both calibration and verification phase respectively, with a highest value of R and PCC equal to 0.836 & 0.8788 and the minimum error of MSE equal to 0.0394. Overall, ELNN-3 shows high accuracy in both calibration and verification phase of the model with the highest R value of 0.9596.

The result of the employed machine learning models were elucidated in Table 3, which shows the outcome of the calibration and verification phase of the model.

Table 3. Result of the machine learning model

Model	Calibration phase					Verification phase				
	R	PCC	MSE	MAE	RMSE	R	PCC	MSE	MAE	RMSE
ELNN-M1	0.8908	0.8838	0.0262	0.1137	0.1620	0.8703	0.8294	0.0454	0.1783	0.2131
ELNN-M2	0.8835	0.8757	0.0432	0.1572	0.2077	0.8695	0.8320	0.0397	0.1903	0.1992
ELNN-M3	0.9596	0.9570	0.0089	0.0719	0.0944	0.9066	0.8775	0.0268	0.1424	0.1638
SVM-M1	0.9166	0.9109	0.0198	0.0971	0.1407	0.8639	0.8303	0.0560	0.1742	0.2365
SVM-M2	0.9126	0.9069	0.0190	0.0957	0.1380	0.8648	0.8289	0.0527	0.1718	0.2295
SVM-M3	0.9279	0.9230	0.0155	0.0916	0.1245	0.8788	0.8436	0.0394	0.1503	0.1985

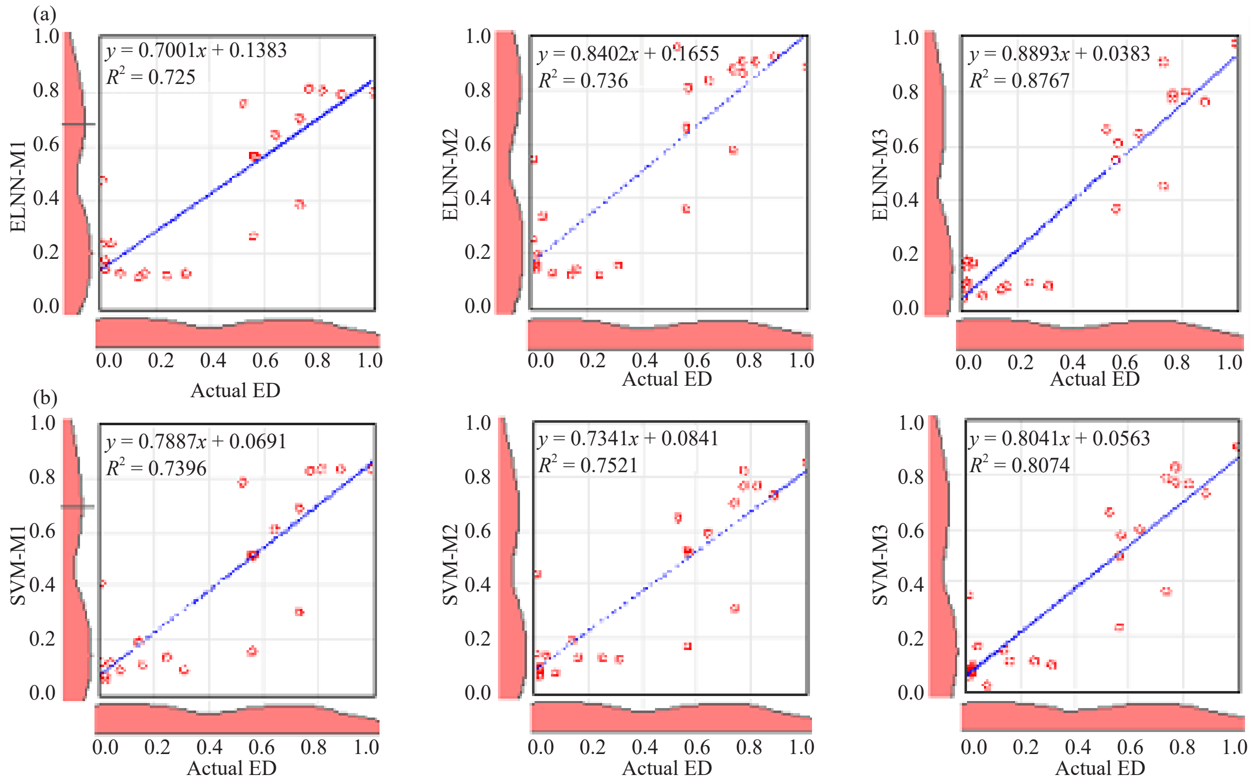

Figure 4. Scatter plots for (a) ELNN model and (b) SVM model

Further discussion of the self-turning model can be visual using graphs. Figure 4 shows the scatter plot which offers a good visual depiction of the relationship between two variables, and they are an essential part of graphical visualization for data analysis. They provide the capacity to find patterns, correlations, and outliers in addition to variable selection and model validation. Using scatter plots makes it easier to interpret data, create hypotheses, and communicate findings, which can be seen from the figure above. ELNN-M3 demonstrates a good fit among the other model combination with a high R value of 0.8767.

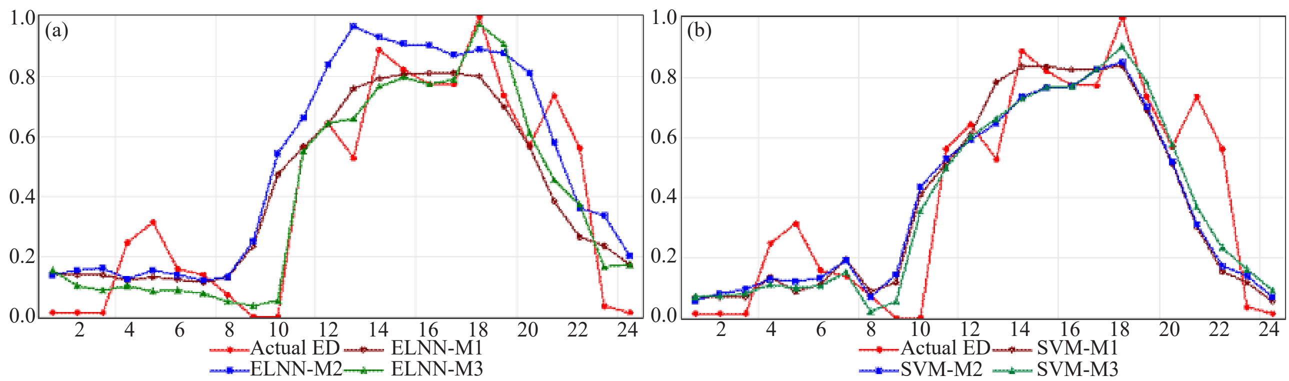

Figure 5. Time series plot for (a) ELNN model and (b) SVM model

Further visualization can be done using a cumulative representation of observations in some temporal scale, called time series plot, where time is usually plotted on the X axis and the values on the Y axis. Such type of plot is used where the main aim is to determine how any given variable is changing with time, and this will enable one to notice some kind of trend, seasonal variation, or even any anomalies. It assists in making predictions, observing trends through time, detecting trends, and making decisions thus being useful in decision making processes and analytical or predictive modeling. Therefore, Figure 5 shows the time series graph of the observed the predicted data during the modeling phase. However, Table 4 shows the comparison state of art for related literature.

Table 4. Review comparison of the related literature

S. No	ML Methodology	Input/Output parameters	Performance evaluation	Comparison performance	References
1	Multilinear regression, Feed forward neural network, Radial basis function neural network (MLR, FFNN, RBFNN)	Inputs: month in year M [-], day in week D [-], mean daily open-air temperature tm [°C], supreme daily outdoor temperature tmax [°C], least daily outdoor temperature tmin [°C], total daily solar emission SD [Wh/ m^2], mean daily wind speed wm [m/s], mean daily relative humidity φd [%]. Outputs: campus daily heating use	R = 0.9701 RMSE = 11,389	Hybrid FFNN with Hybrid RBFN model performed better and gives an excellent result.	[34]
2	Particle swarm optimization, Genetic algorithm, Radial basis function neural network (PSO, GA, RBFNN)	Inputs: business as usual, planning scenarios Outputs: trade-off scenario	The electricity need of Wuhan will increase to 95.85 billion kWh with an annual average growth rate of 11.5%	RBF performs better than the rest of the ANN models	[35]
3	Adaptive neuro fussy inference system, Long short term memory (ANFIS, LSTM)	Inputs: population, cross-over rate, mutation rate Outputs: generation	R = 0.9868, RMSE = 613.95	LSTM estimation gives a well output better than the ANN trained with met heuristic algorithm, achieve excellent result in all metrics performance.	[36]
4	Artificial neural network, Decision tree, Support vector machine (ANN, DT, SVM)	Inputs: same as ANN Outputs: energy consumption kWh/m^2	RMSE = 0.66, MAE = 2.20	ANN performs similarly to SVM with slightly lower RMSE and MAE, while decision tree give the worst output value.	[37]
5	Artificial neural network, Support vector machine, Long short term memory (ANN, SVR, LSTM)	Inputs: same as ANN, LSTM, SVR Outputs: mean temperature and mean humidity	R = 0.918, RMSE = 3531%	LSTM gives the excellent fit of the prediction among the other models.	[38]
6	Multi-layer perception, Support vector regression (MLP, SVR)	Inputs: heating loads Outputs: cooling loads	R = 0.9993 RMSE = 0.4832	MLP method gives the highest prediction with the highest value of R.	[39]
7	CNN-LSTM, XGboost, LSTM, RBFN	Inputs: same as CNN-LSTM Outputs: short-term electrical load forecasting	MAE = 370.18 RMSE = 434.4985	The projected CNN-LSTM model provides the lowest values of MAE, RMSE, and MAPE compared to LSTM, RBFN, and XGboost models. Also, the R^2 values of CNN-LSTM are the highest among the four models, which make it to be the best performing model.	[40]

The current study demonstrates that, the Elman Neural Network (ELNN) with the M3 combination of input variables (wind speed, temperature, and solar radiation) attained a correlation coefficient (R) of 0.9596 and RMSE of 0.0944 during the calibration phase. This is consistent with the findings of [19], who employed an Artificial Neural Network (ANN) model for energy demand prediction in Wuxi City, China, and conveyed an RMSE of 1.58%. While both studies used ANN models, our model performed better in terms of RMSE, which could be attributed to our presence of Load demand as a predictive variable, enhancing model accuracy. Likewise, [16] used a Long Short-Term Memory (LSTM) model for building energy demand forecasting and achieved a marginally lower accuracy (R = 0.918) compared to our ELNN-M3 model. This could be due to the sequential structure differences between the datasets or the specific variables measured. While both studies highlighted the importance of using machine learning models for energy demand prediction, the current work emphasizes the utility of the ELNN model in predicting energy demand in tropical urban environments, where factors like solar radiation significantly impact consumption patterns. Compared to the study [20], which employed a Random Forest (RF) algorithm, we observed that our ELNN model outperformed RF in terms of predictive accuracy (R = 0.9596 vs. R = 0.897). This further freezes the argument that neural network models, particularly ELNN, are better suited for energy demand prediction tasks where non-linear relationships between variables play a critical role.

4. Conclusion

It is important to understand how different methods are used for calculating energy demand by evaluating the methodologies for energy demand forecasting, which is also critical and foundational to the study of power systems. An overview of ELNN and SVM-based models for forecasting energy demand changes in Lagos State, Nigeria is presented in this study. In order to enhance the inputs, a non-linear approach involving identifying three model combinations was selected including M1, M2, and M3. That is, the ELNN-M3 model had a better result than the other models and got the maximum R = 0.9596. Table 3 above shows the projected total population for the study region reaches 9,596 by the time of writing this report. Specifically, to fill this gap, data with the 24-hour time series was used in the study, and the performance measures R, PCC, MSE, MAE, and RMSE were employed. Given that there has been no previous study forecasting energy demand in Lagos State, Nigeria, this work will add value to the existing literature. Furthermore, it provides basic information on how current and future (known and potential) energy resources can be managed to support social and economic development of the region as well as to improve the quality of life of the people.

Conflict of interest

The authors declare no competing financial interest.

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