Energy Demand Forecasting for Hybrid Microgrid Systems Using Machine Learning Models

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Abstract

This study aims to design energy demand forecasting models for energy management in hybrid microgrid systems using optimized machine learning techniques. By incorporating temperature, humidity, season, hour of the day, and irradiance, the complex relationship between these input parameters and the yield of photovoltaics, generator, and grid energy sources is examined. Five different machine learning models including linear regression, random forest (RF), support vector regression, artificial neural network, and extreme gradient boosting models are adopted in this study. Evaluation of model performance shows that the RF model is the best candidate for the dataset, with a mean-squared error of 0.2023, mean absolute error of 0.0831, root-mean-squared error of 0.4498, and R^2 score of 0.9992. Shapley additive explanations analysis identified key predictors such as hour, irradiation, and season while highlighting the negative impact of humidity and day of the week on energy demand.

Keywords: energy demand, forecasting, hybrid microgrid, machine learning

1. Introduction

To properly size their energy supply systems, institutions need precise energy demand forecasts. Global electric power systems depend on load forecasts for energy trading, operational strategies, and planning. Deregulation and competitive markets have transformed traditional sectors, and the Kyoto Protocol mandates both a reduction in carbon emissions and an increase in renewable energy integration, which are crucial for energy sustainability [1]. Renewable sources are intermittent and affected by weather, while electricity demand varies with weather, population distribution, and lifestyle patterns, necessitating accurate forecast models for proper energy system sizing [1, 2]. Integrating renewable energy into power systems adds complexity, and creates challenges in maintaining energy balance [3]. Therefore, to balance supply and demand, reduce operation costs, and increase energy system reliability, energy demand forecasting is crucial. In hybrid microgrid systems, which integrate non-renewable energy with renewable energy sources, this task becomes even more complex [4]. Because of their unpredictability and uncertainty, renewable energy sources require sophisticated forecasting models capable of handling large datasets and identifying intricate patterns in energy usage. Energy demand forecasting has shown significant potential with machine learning models. Linear regression (LR) is effective for predicting demand when variable relationships are linear [5], while random forest (RF) offers excellent capability in handling large datasets with multiple features for regression [6].

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Support vector regression (SVR), on the other hand, is noted for its robustness against overfitting, particularly with variable data [7, 8]. Meanwhile, artificial neural network (ANN) models benefit from enhanced predictive accuracy and convergence when optimized using the ADAM optimizer [9, 10].

Recent research highlighted the use of machine learning (ML) models for forecasting energy consumption, with Sun-Youn Shin et al. [11, 12] showing that, while traditional econometric models may outperform ML models in stable conditions, ML models excel with irregular time series data. However, to interpret ML model efficiency and identify input parameters that influence energy demand, Shapley additive explanations (SHAP), a game-theory-based analysis, is used [13]. ML models find diverse applications in the literature. The efficacy of the ANN model is emphasized by Narayan et al. [14] who designed an improved radial basis function neural network (RBFNN) with parameters optimized using particle swarm optimization (PSO) for pitch control of rated power generators, Adeer Khan and Mehran Sudheer [15] adopted RF for classification of land use land cover (LULC) maps for supporting better planning and urbanization of cities. Similarly, Dhaked et al. [8] adopted RF to forecast fuel cell deterioration in proton exchange membrane fuel cells. Additionally, Dhaked et al. [12] in another study, proposed long short-term memory (LSTM) to forecast PV output for energy management. Overall, this body of literature demonstrates the effectiveness of ML models across various applications. Energy demand forecasting in microgrid systems is essential for efficient operations.

A review by Raniya [16] presents a comparative analysis of artificial neural networks, ML, and deep learning forecasting techniques, highlighting their effectiveness in forecasting energy demand and renewable energy sources. In the same vein, ANN optimized by Levenberg-Marquardt optimization is proposed for forecasting in cluster microgrids by Sivakavi et al. [17]. Similarly, Rasha M. Abd El-Aziz [18] proposed hybrid machine learning which integrates multilayer perceptron (MLP), SVR, and the catboost algorithm for the prediction of energy consumption in renewable energy sources, results show that the proposed model outperformed the existing models. David Mhlanga [19] assesses the potential of deploying artificial intelligence (AI) and ML models for energy consumption and emphasizes the potential benefits of AI and ML for the energy sectors, especially for developing nations. R. Sing et al. [20] used SVR for energy management and forecasting of wind and solar power generation, leveraging historical weather data. Despite these advancements, ML models for the multioutput forecast of the energy yield from multiple sources to meet the energy demand in microgrid systems with diverse energy sources remain limited, making this study a valuable contribution to the field.

This proposed study aims to develop machine learning models for effectively forecasting energy demand in a hybrid microgrid system. By employing the RF model, the research will address the challenge of predicting multiple energy source yields to meet energy demands, with the objective of achieving superior prediction accuracy and system performance compared to existing models. The proposed approach will be tested using energy demand data from the Nile University of Nigeria in Abuja, with the goal of adapting the model for similar energy systems with comparable datasets. The methodology for this proposed research will be detailed in Section 2, the expected results and their significance will be outlined in Section 3, and the anticipated contributions to the field will be summarized in Section 4.

2. Methodology

This research is structured into four main phases: data collection, data processing, machine learning model development, and hyperparameter optimization, concluding with SHAP analysis. The data collection methodology, detailed by Zarma et al. [21], develops a comprehensive dataset through various qualitative and quantitative techniques. After collection, the data is rigorously processed to handle missing data, normalize values, and transform variables for improved model performance. Several machine learning algorithms are explored to identify the most effective model based on the dataset's characteristics and research objectives. Furthermore, hyperparameter optimization is applied to fine-tune model parameters for enhanced accuracy and generalization. Finally, SHAP analysis is deployed to interpret model predictions, offering insights into feature contributions and underlying data patterns. In summary, Fig. 1 illustrates case the different stages in the study, from data collection and processing to data splitting, model development, optimization, and SHAP analysis.

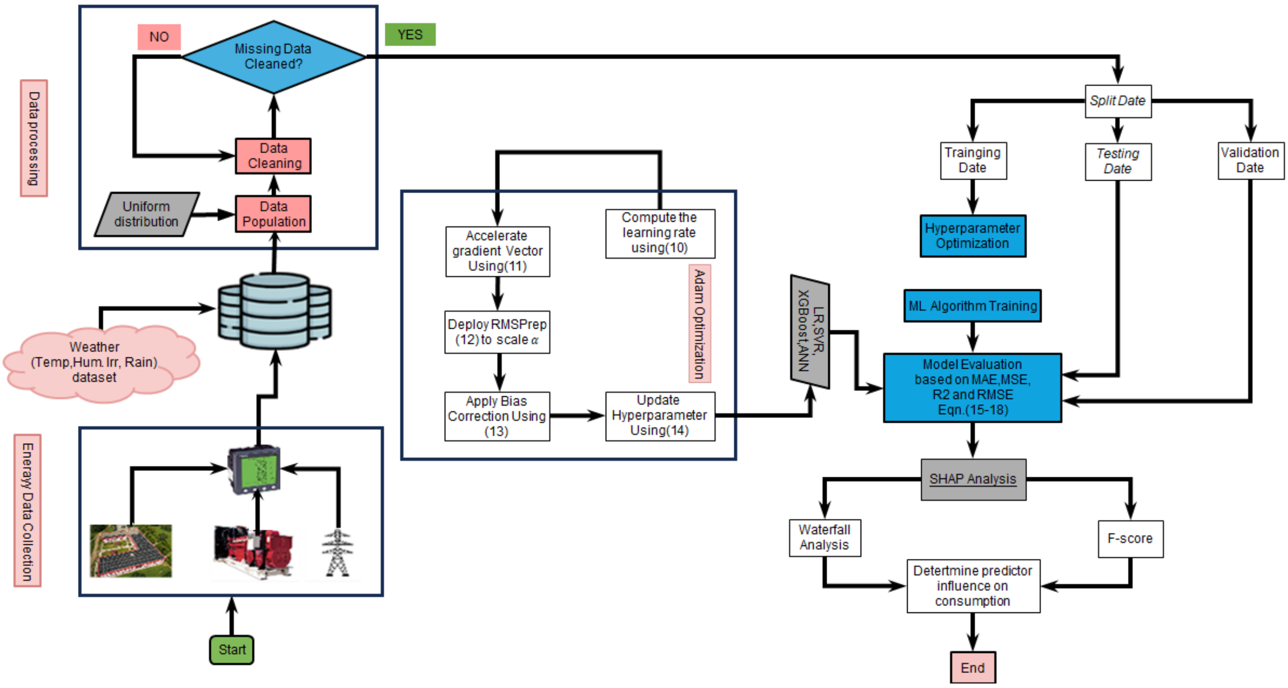


Fig. 1 Methodology of the study

The monthly energy contributions from the three sources on the campus over eight months are shown in Fig. 2. It can be observed that almost every month, the Abuja electricity distribution company (AEDC), which is the public utility grid, is the largest energy contributor, followed by the diesel generators, and lastly the PV system.

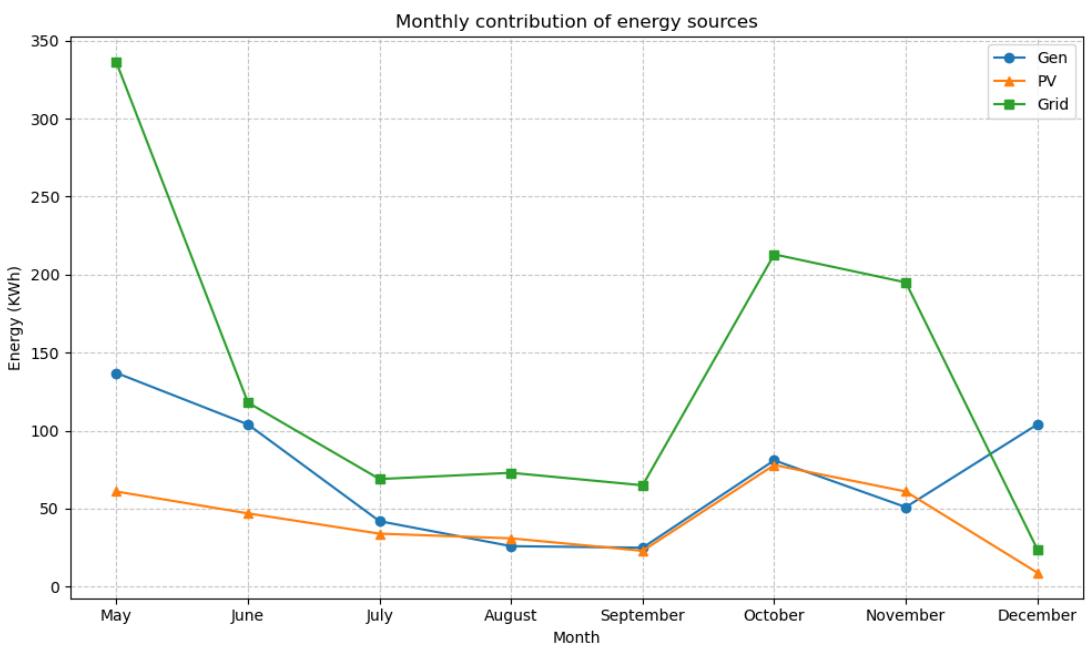


Fig. 2 Monthly contribution of energy sources

2.1. Dataset population

Populating datasets is crucial for effective statistical analysis, machine learning modeling, and decision-making, as it enables robust analysis, enhances interpretability through techniques such as SHAP, improves model training, and facilitates data visualization, leading to more reliable insights and informed decisions.

Accordingly, distinguishing between peak and off-peak times is vital for energy management and optimizing resource allocation and pricing strategies for power stations [22]. Therefore, the collected dataset is populated using a normal distribution given by.

$$f(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

Therefore, using a normal distribution given by Eq. (1) and a simulation of Nile University of Nigeria's energy demand from 6 a.m. to 6 p.m., the peak and off-peak demand values are randomly generated using Eq. (2) within the threshold of daily consumption given by Eq. (3). Ultimately, 4,928 data points are generated accordingly for the ML models.

$$x_i \sim N(\mu, \sigma^2) \tag{2}$$

$$T = \mu + k \cdot \sigma \tag{3}$$

where *N* is the normal distribution function, μ represents the mean, σ is the standard deviation of the day in view, k is the scaling factor, and *T* is the energy threshold of consumption.

2.2. Dataset description

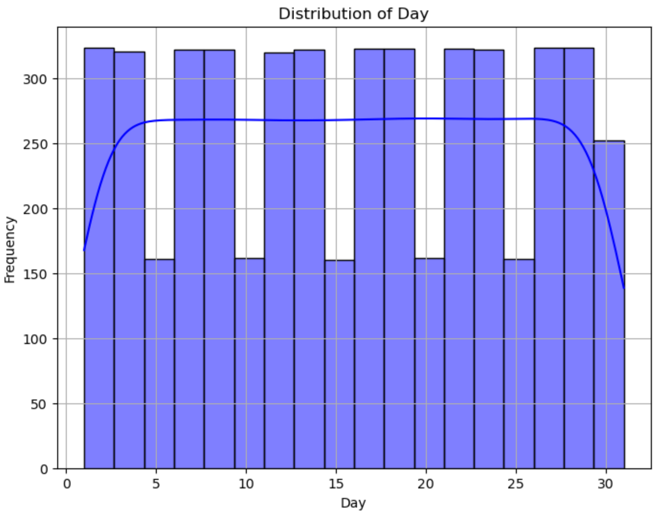
The data description provided in Table 1, which summarizes descriptive statistics such as count, mean, standard deviation (SD), minimum (min), maximum (max), and percentiles, is essential for creating machine learning models [23]. It aids in identifying missing values, detecting outliers, and interpreting data distribution, which enables prudent preprocessing decisions for accurate modeling.

Table 1 Statistical description of the dataset

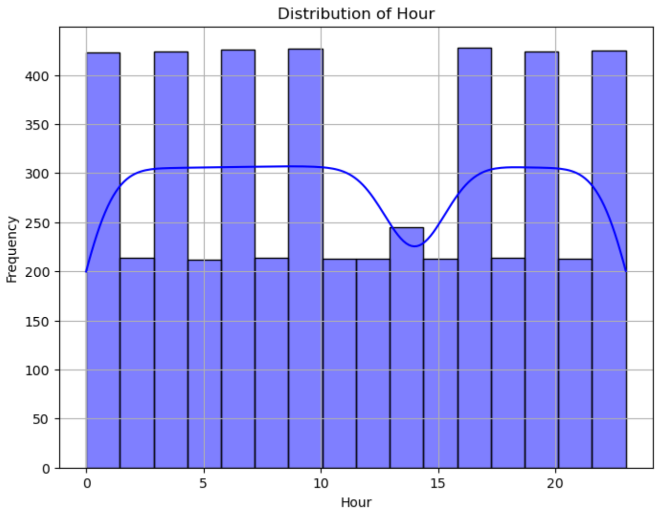
data descriptor	predictors								target output			
	day	hour	month	season	temp	humidity	Irr.	rain	gen (MWh)	grid (MWh)	PV (MWh)	total (MWh)
count	4,928	4,928	4,928	4,928	4,928	4,928	4,928	4,928	4,928	4,928	4,928	4,928
mean	16	11	8	2	29	60	47	10	16	21	5	42
SD	9	7	2	1	7	10	53	3	10	13	6	29
min	1	0	5	1	10	30	0	1	3	5	0	8
25%	8	5	6	1	24	53	0	8	7	9	0	16
50%	16	11	8	2	29	60	0	10	9	14	0	24
75%	23	18	10	3	34	67	93	12	24	30	10	65
max	31	23	11	3	42	90	150	19	35	50	30	115

2.3. Data distribution

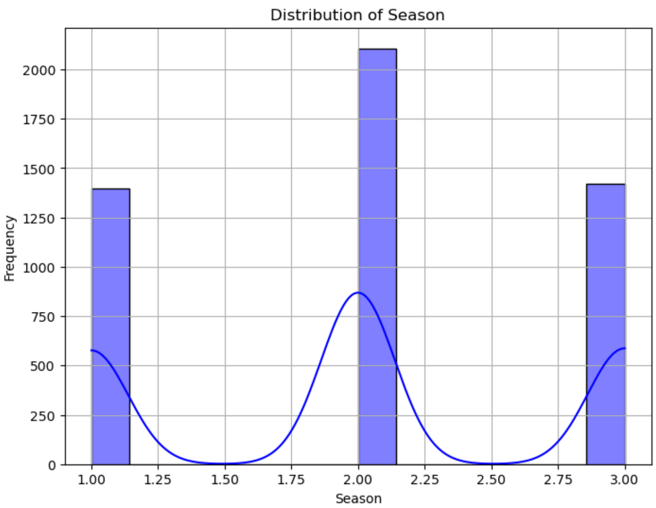
Examining the distribution of input predictors is essential for understanding their influence on the energy demand forecasting model [24]. The data reveals significant variability across different hours of the day, as illustrated in Fig. 3(a), along with moderate fluctuations in daily energy consumption patterns throughout the week, as depicted in Fig. 3(b). Seasonal effects, particularly during the harmattan season [Fig. 3(c)] and distribution of rainfall [Fig. 3(d)], play a key role in evaluating energy demand. Additionally, understanding the impact of temperature and solar irradiation (Irr.) on energy consumption is critical, as shown in Fig. 3(e) and Fig. 3(f), where temperatures range from 10°C to 42°C, displaying both broad and moderate variability.



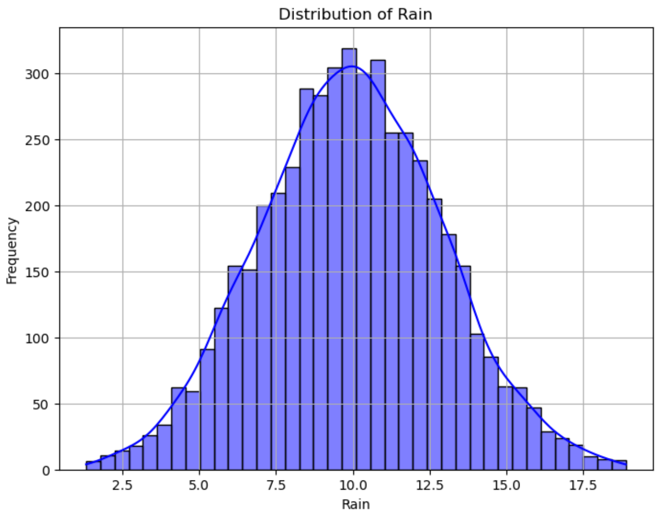
(a) Day of the week



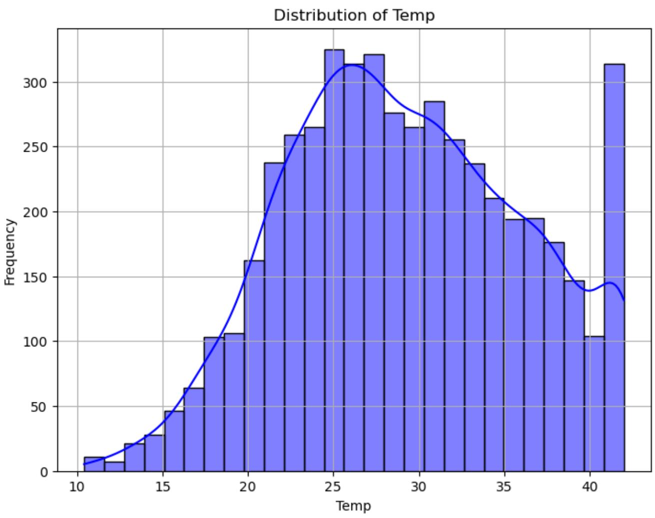
(b) Hour of the day



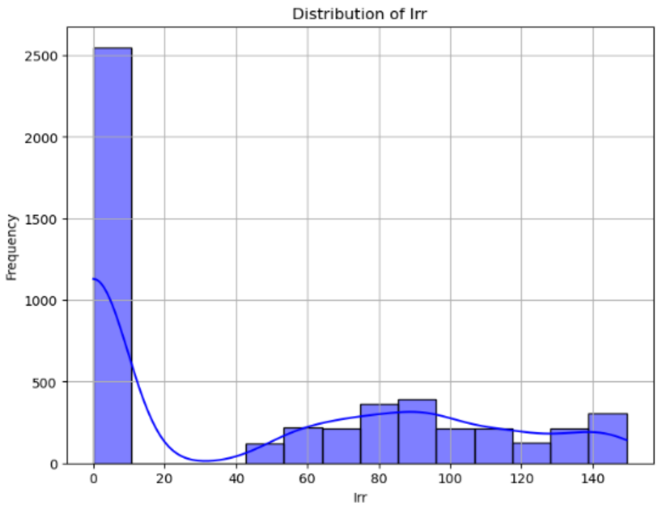
(c) Season



(d) Rain



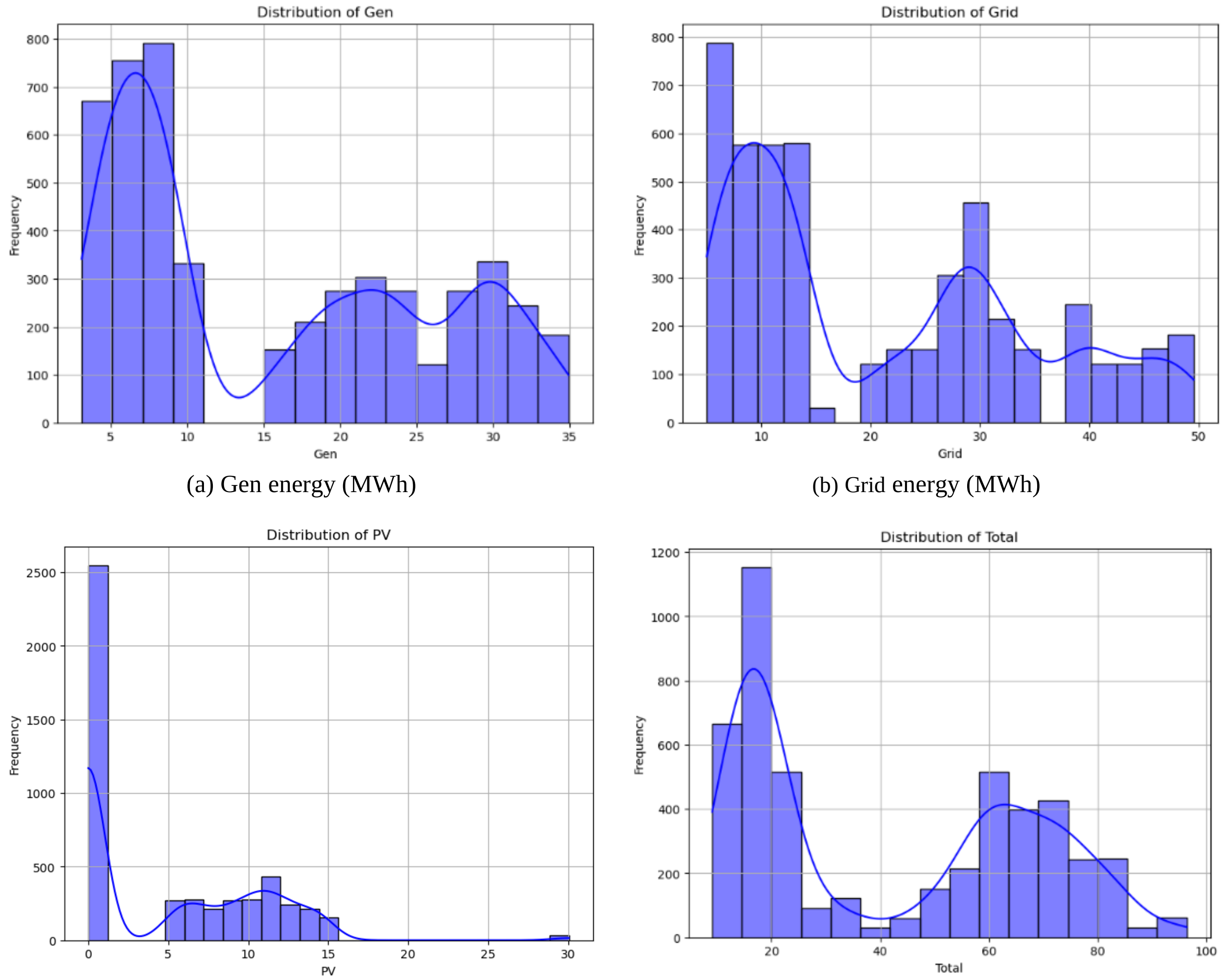
(e) Temperature



(f) Irradiation

Fig. 3 Distribution of input predictors

Similarly, the distribution of the target response is shown in Figs. 4(a)-(d). However, the high standard deviations in AEDC, as shown in Fig. 4(b), and total energy mentioned in Fig. 4(d) indicate significant fluctuations due to factors such as temperature and humidity, while the minimum and maximum values are essential for detecting outliers and guiding data transformation.



(a) Gen energy (MWh) (b) Grid energy (MWh)

(c) PV energy (MWh) (d) Total energy (MWh)

Fig. 4 Distribution of target outputs

2.4. Modeling of energy demand forecast modeling

This section presents the machine learning models proposed in this study, starting with the simplest model, LR, which serves as a baseline for understanding the relationship between input features and the target outputs. Following LR, SVR is explored to enhance predictive performance by mapping inputs into higher-dimensional spaces. The study also incorporates more advanced models, such as extreme gradient boosting (XGBoost) for efficient and powerful boosting capabilities, and ANN for capturing complex, non-linear patterns in the data. Lastly, RF is employed for its robustness and ability to handle large datasets with high variance, providing a comprehensive approach to model development and performance evaluation.

2.4.1. Linear regression

The first model proposed for analyzing energy consumption is linear regression, which is one of the most basic and widely used statistical methods in machine learning and data analysis. LR determines the relationship between the yield of the PV system, gens, and public utility grid, and the observed data for temperature, humidity, season, holidays, and hour of the day by fitting a linear equation expressed by

$$\hat{y} = w_0 + w_1 T + w_2 H + w_3 S + w_4 h + w_5 d \tag{4}$$

where $\hat{y}$ is the predicted response, w_0, w_1, w_2, w_3, w_4, and w_5 are the weights associated with each feature, and T, H, S, h, and d represent temperature, humidity, season, hour of the day, and a binary variable for holidays, respectively.

2.4.2. Support vector machine

SVR is the second forecasting model. It uses a subset of training data to optimize the best-fit position and finds the hyperplane with the maximum margin to distinguish classes. In this work, the radial basis function (RBF), which compares data points based on their Euclidean distance, is adopted as the Kernel function to predict the target output given by

$$\hat{y} = \sum_{i=1}^{N} \alpha_i \cdot K((T_i,\ H_i,\ S_i,\ h_i,\ d_i), (T,\ H,\ S,\ h,\ d)) + b \tag{5}$$

where $\hat{y}$ is the predicted output, H_i, S_i, h_i, d_i represent the support vectors of the input predictors (temperature, humidity, season, hour of the day, and holidays), K is the kernel function, α_i is the learning rate, and b is the bias term.

2.4.3. Random forest

The random forest algorithm is a robust machine learning technique that builds multiple decision trees using random subsets of data and features, averaging their outputs to make predictions. This ensemble approach enhances accuracy and consistency. Systematically, each decision tree takes the input predictors to produce a prediction based on node splits, as shown in Eq. (6). Subsequently, the RF aggregates the predictions from multiple decision trees to generate the final target output prediction, as presented in Eq. (7).

$$\hat{y}_i = \mathrm{D}_i(T,\ H,\ S,\ h,\ d) \tag{6}$$

$$\hat{y} = \frac{1}{N} \sum_{t=1}^{N} \hat{y}_i \tag{7}$$

where $\hat{y}$ is the predicted output, D_i represents each decision tree for each input predictor (T, H, S, h, d), N is the number of trees, and $\hat{y}_i$ is the output of each tree.

2.4.4. Artificial neural network

Neural networks autonomously learn mappings from inputs to outputs through interconnected layers of neurons, using forward propagation to adjust weights, biases, and activation functions. This process, guided by backpropagation, minimizes output error by iteratively adjusting parameters to reduce discrepancies between expected and actual outputs. Training involves minimizing the loss function, such as mean squared error or cross-entropy, to improve model accuracy and performance. The output of the model is determined by

$$\hat{y} = f(W \cdot (T,\ H,\ S,\ h,\ d) + b) \tag{8}$$

where $\hat{y}$ is the target output, W is the weight matrix, (T, H, S, h, d) are the input predictors, b is the bias, and f is the activation function

The activation function's role is to introduce nonlinearity into the neural network. Activation functions have a range of types, including sigmoid, tanh, and rectified linear units (ReLU). Meanwhile, the ReLU as expressed in Eq. (9) is chosen because of its simplicity and robustness as the activation function in this study.

$$f(x) = \begin{cases} 0, & x<0 \\ x, & x\geq 0 \end{cases} \tag{9}$$

2.4.5. Extreme gradient boosting (XGBoost)

The regression tool XGBoost uses the concept of gradient boosting to forecast continuous values. In this process, decision trees are constructed iteratively to minimize the loss (typically squared error) between the predicted and actual values. XGBoost optimizes the model through advanced techniques such as shrinkage, tree pruning, and regularization (L1 and L2) which help prevent overfitting and enhance generalization. It can handle missing data effectively and performs especially well with large datasets.

2.5. Hyperparameter optimization using adaptive moment estimation

The adaptive moment estimation (ADAM) optimization algorithm, introduced by Kingma and Ba in 2014 [10], combines the benefits of the adaptive gradient algorithm (AdaGrad) and root mean square propagation (RMSProp) and has emerged as one of the most widely used techniques for training deep learning models. Its adaptive learning rate capabilities render the suitability for training deep neural networks. ADAM calculates adaptive learning rates for each parameter by estimating the first and second moments of the gradients as presented in Eq. (10).

$$\theta_{t+1} = \theta_t - \alpha \cdot \nabla_\theta J(\theta_t) \tag{10}$$

where $\hat{y}$ is the model parameter, α is the learning rate, and $J(\theta_t)$ is the cost function.

To accelerate a gradient vector in the correct direction, thereby accelerating convergence, the momentum update rule is determined by Eq. (11). Furthermore, adopting the RMSProp-based ADAM optimization technique, the learning rate of the ANN model is determined by Eq. (12).

$$v_t = \beta_1 \cdot v_{t-1} + (1-\beta_1) \cdot g_t \tag{11}$$

$$s_t = \beta_2 \cdot s_{t-1} + (1-\beta_2) \cdot g_t{}^2 \tag{12}$$

where v_t is the moving average of the gradient, β_1 is the decay rate, g_t is the gradient at time step t, s_t is the moving average of the squared gradient, and β_2 is the decay rate for the squared gradient.

Additionally, the bias correction in ADAM is used to adjust the initial bias in the first and second moment estimates as shown in Eq. (13). The final parameter update rule for ADAM is determined using Eq. (14).

$$\begin{aligned} \hat{v}_t &= \frac{v_t}{1-\beta_1{}^t} \\ \hat{s}_t &= \frac{s_t}{1-\beta_2{}^t} \end{aligned} \tag{13}$$

$$\theta_{t+1} = \theta_t - \alpha \frac{\hat{v}_t}{\sqrt{\hat{s}_t}} \tag{14}$$

2.6. Model evaluation

The performance of machine learning models is evaluated using statistical metrics such as RMSE, MAE, MSE, and R2. These metrics are essential for evaluating model accuracy and understanding how individual input factors affect model predictions. Accordingly, these metrics are determined by Eqs. (15)-(18) respectively.

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(y_i - \hat{y}\right)^2} \tag{15}$$

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|y_i - \hat{y}\right| \tag{16}$$

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(y_i - \hat{y}\right)^2 \tag{17}$$

$$R^2 = 1 - \frac{\sum\left(y_i - \hat{y}\right)^2}{\sum\left(y_i - \bar{y}\right)^2} \tag{18}$$

where y_i is the actual observation, $\hat{y}$ is the estimated observation, and $\bar{y}$ the mean value of y_i

2.7. Validation of proposed models

To develop and evaluate the prediction model, the dataset is split into training (80%) and testing (20%) sets. The testing set is used to evaluate the model's accuracy after it is trained on the training set. This split technique is chosen due to its track record of producing strong generalizations.

2.8. Shapley explanations

SHAP is a widely used method for interpreting machine learning model predictions by calculating Shapley values for each feature, which indicate the feature's contribution to a prediction [25]. Rooted in cooperative game theory, SHAP employs an additive attribution technique to quantify each feature's relative impact on the model's output. This method is particularly valuable for understanding complex models, such as deep neural networks, by clarifying the underlying logic of predictions. In this study, SHAP analysis is used to assess how predictors influence model prediction accuracy.

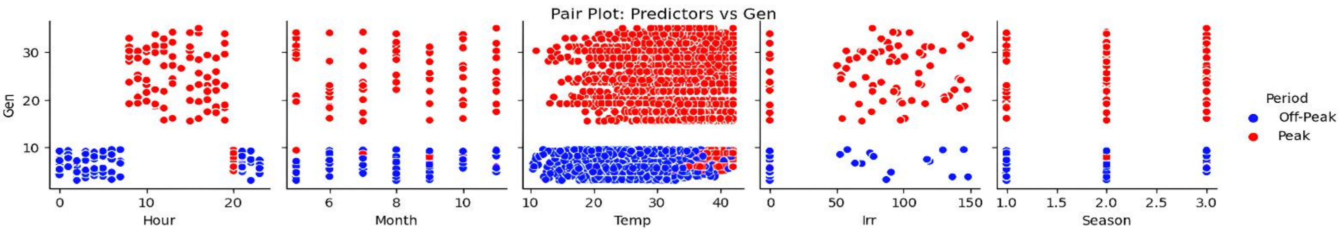
3. Results and Discussion

This section explores various data analysis techniques used in the study, starting with pair plots to visualize the relationships and distributions between variables. It then discusses the optimization of hyperparameters to enhance model performance and accuracy. The analysis also includes Spearman correlation to measure the strength and direction of associations between features.

Additionally, feature importance is assessed to identify the most influential variables, supported by SHAP waterfall plots that provide detailed insights into feature contributions. A comparison of model performance metrics is conducted to evaluate and rank each model's effectiveness, and scatter plots are utilized to visually compare predictions against actual values, further validating model accuracy.

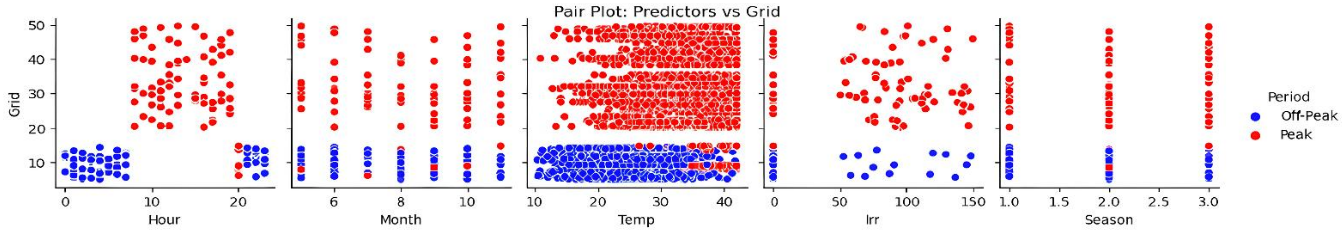
3.1. Predictors and target relation

The study examines how target variables (gen energy, grid energy, PV energy, and total energy) interact with the predictors (hour, month, season, temperature, and irradiance). A pairplot is utilized to visualize the relationships between the predictors and targets Fig. (5).

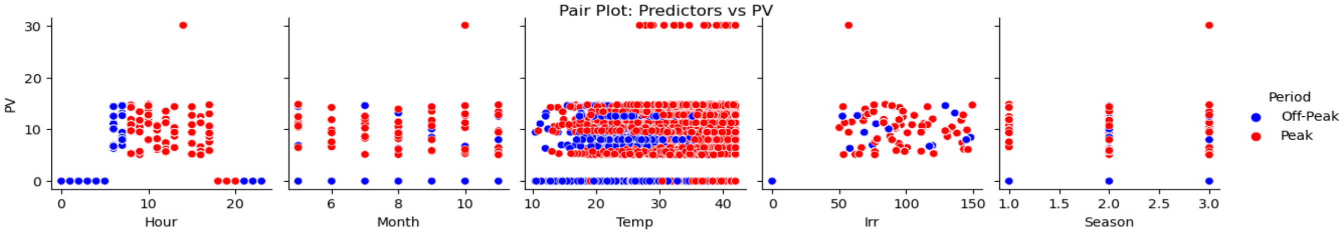


(a) Pairplot of input predictors against gen energy

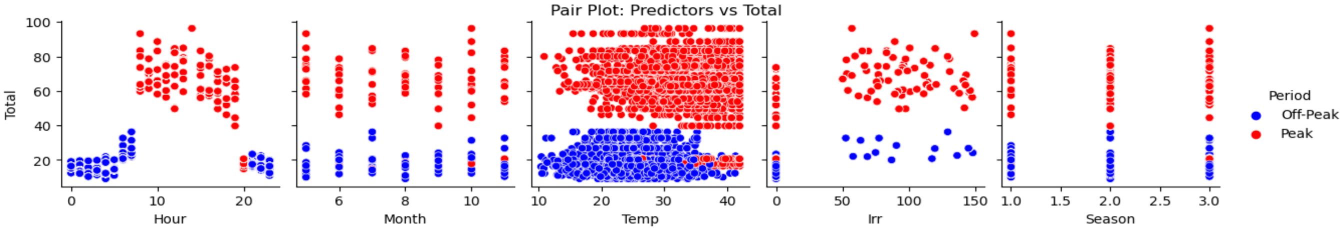
Fig. 5 Pairplot of predictors vs target output



(b) Pairplot of input predictors against grid energy



(c) Pairplot of input predictors against PV energy



(d) Pairplot of input predictors against total energy

Fig. 5 Pairplot of predictors vs target output (continued)

Additionally, irradiance and temperature show a multimodal relationship with the target outputs, influenced by seasonal variations, indicating that energy consumption has different peaks across the seasons.

3.2. Hyperparameter optimization

Selecting hyperparameters is essential for optimizing ML model performance, as it enhances model effectiveness, reduces computational costs, and ensures robustness and adaptability.

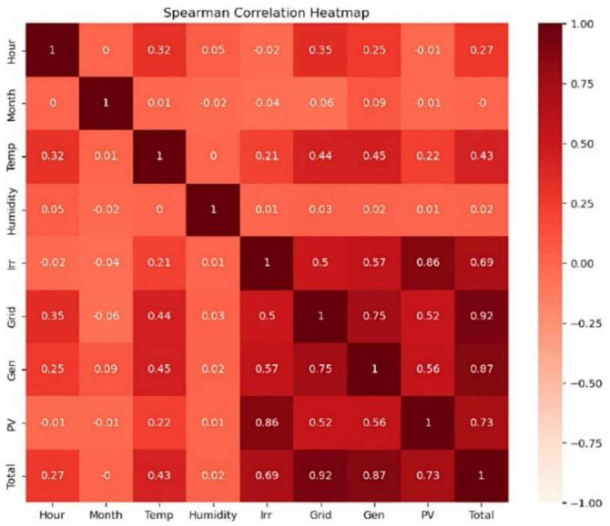
Table 2 Optimized hyperparameters

Model	ANN						
Hyperparameter	Hidden layers	Learning rate	Dropout rate	Activation functions	Optimizer	Batch size	Epochs
Value	480	0.0001	0.2	ReLU	ADAM	32	400
Model	SVR						
Hyperparameter	kernel	C	Gamma	Epsilon	Optimizer		
Value	'rbf'	1	0.1	0.1	Grid search		
Model	RF						
Hyperparameter	Bootstrap	Criterion	Max depth	Max features	Optimizer	Max leaf nodes	n_Estimator
Value	TRUE	Squared error	None	1	Grid search	None	100
Model	XGBoost						
Hyperparameter	objective	Learning rate	Subsample	Max depth	Optimizer	alpha	n_Estimator
Value	Squared error	0.1	0.3	5	gbtree	5	100

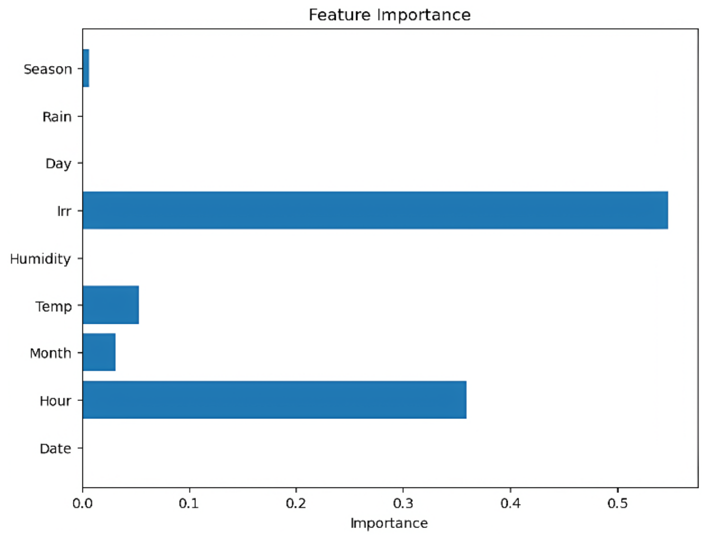
Thus, the optimized hyperparameters for the models adopted in this study are shown in Table 2. The ANN model is configured with 480 hidden neurons, a learning rate of 0.0001, a dropout rate of 0.2, ReLU activation, and the ADAM optimizer, trained using a batch size of 32 over 400 epochs. Similarly, the SVR model utilizes an RBF kernel, with hyperparameters C=1, Gamma=0.1, and Epsilon=0.1, tuned through grid search. Furthermore, the RF model uses 100 estimators, bootstrapping, squared error as the split criterion, and no maximum depth, with hyperparameter tuning conducted via grid search. Likewise, the XGBoost is implemented with a gbtree objective, a learning rate of 0.1, a max depth of 5, a subsampling rate of 0.3, and L1 regularization (Alpha=5) across 100 estimators. Each model is systematically optimized to enhance predictive accuracy while minimizing overfitting.

3.3. Predictor score and correlation matrix

The analysis of energy consumption at Nile University, illustrated in Fig. 6(a) using the Spearman correlation matrix, reveals significant connections between various factors and energy usage. Grid energy shows the highest correlation with total consumption (0.992), followed by generator energy (0.87) and solar PV energy (0.73). Irradiance (sunlight) emerges as the most correlated factor among the energy sources, with temperature, time of day, and month also playing important roles. As shown in Fig. 6(b), the feature importance plot confirms irradiance as the most influential factor in forecasting energy consumption, with temperature, month, and season following, highlighting the impact of environmental and temporal conditions on energy demand.



(a) Correlation matrix of predictor



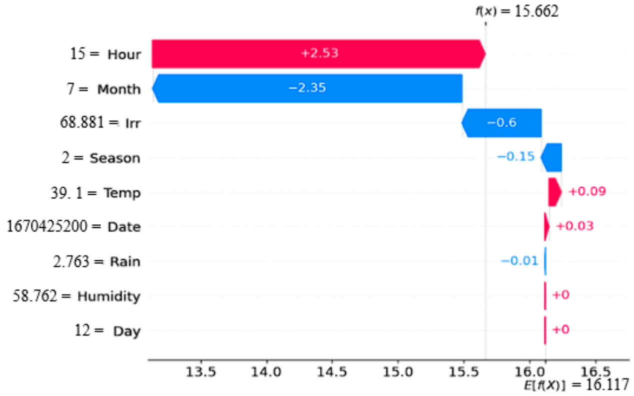
(b) Feature importance of input predictors

Fig. 6 Feature importance and correlation matrix of predictors

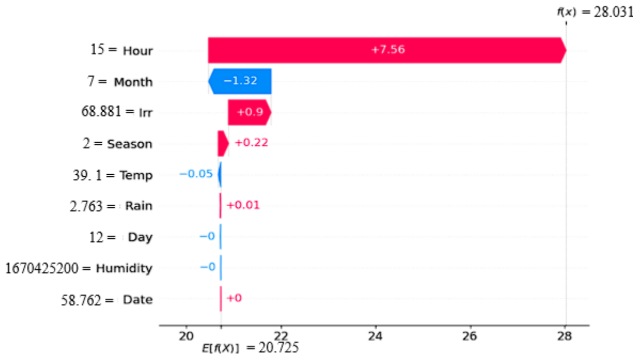
3.4. Shapley additive explanations interpretation (SHAP)

The feature importance plots in the previous section highlight the contribution of each feature to overall model accuracy, while the SHAP plots explain how individual features influence specific predictions. SHAP values adjust the base value, which is the average prediction, to determine the final forecast.

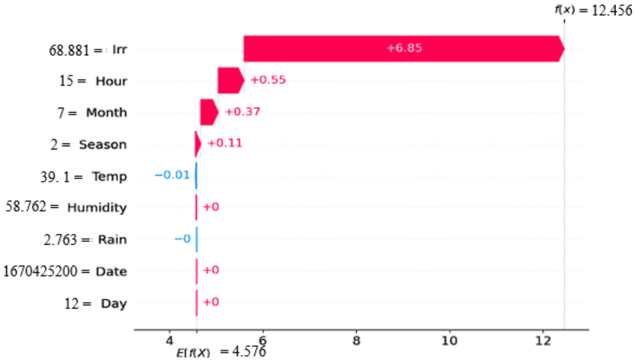
In Fig. 7(a), "Hour" increases predictions by +2.53, while "Month" reduces them by -2.35, with smaller impacts from irradiance, season, and temperature. Fig. 7(b) shows that for AEDC energy, "Hour," irradiance, and season positively influence predictions, while "Month" and temperature decrease them. Fig. 7(c) indicates positive contributions from most predictors, except rain and temperature. Fig. 7(d) reveals negative influences from month, day, and humidity on total energy predictions. Final predictions are 15.662 (gen), 28.031 (AEDC), 12.456 (PV), and 56.15 (total energy), compared to the expected values of 16.117, 20.725, 4.576, and 41.418, respectively.



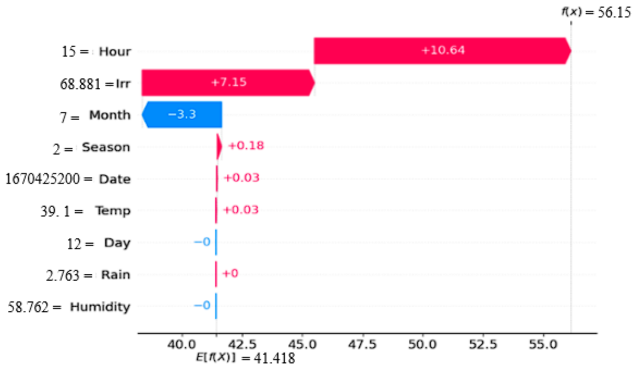
(a) SHAP values of predictors against gen energy



(b) SHAP values of predictors against AEDC energy



(c) SHAP values of predictors against PV energy



(d) SHAP values of predictors against total energy

Fig. 7 SHAP plots of predictors' influence on proposed models' prediction accuracy

3.5. Metrics evaluation comparison

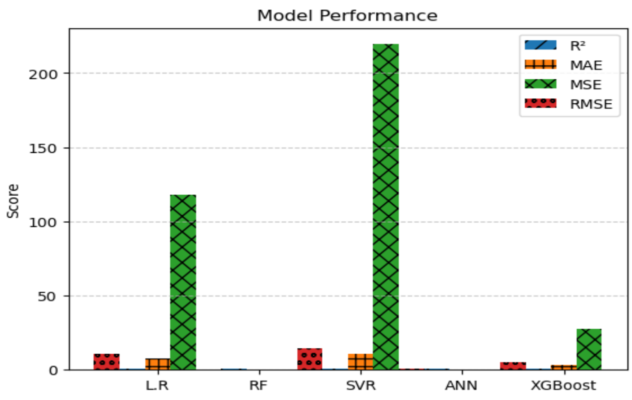
To predict the energy contributions of sources in use by power station one of Nile University of Nigeria, five machine learning models are evaluated, including LR, SVR, XGBoost, ANN, and RF. The performance metrics for these models are summarized in Table 3, with the ANN model achieving an MSE of 0.2023, MAE of 0.0831, RMSE of 0.4498, and R^2 score of 0.9992. A low MAE indicates that the RF model's predictions are generally close to actual values, while a low MSE reflects high overall prediction accuracy with minimal large errors. A high R^2 score demonstrates that the model effectively explains a significant portion of the variance in the target variable, confirming a good fit to the data.

Table 3 Model performance evaluation

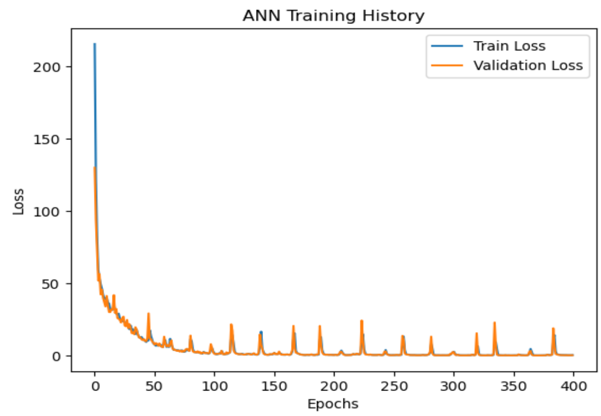
S/N	Models	Metrics			
		R^2	MSE	MAE	RMSE
1	LR	0.5176	118.2013	7.4557	10.8720
2	SVR	0.6729	219.4103	10.7714	14.8125
3	XGBoost	0.8949	27.8321	3.4542	5.2756
4	ANN	0.9975	0.4603	0.4048	0.6784
5	RF	0.9992	0.2023	0.0831	0.4498

Furthermore, comparing the proposed model to the existing literature, the proposed model also performed as expected. In a similar study by P. W. Khan et al. [26] which utilizes renewable and non-renewable energy sources to power loads in Korea, the hybrid ML model achieves an MAE of 15.72 and MSE of 472.9644 while the R2 metric is not evaluated for the model. Additionally, Navid et al. [27] proposed a medium-term forecast using ML modes, where the R2 metrics ranged between 0.93 and 0.96, highlighting the effectiveness of the proposed model in this work.

The ranking of the metric parameters is illustrated in Fig. 8(a) the root mean square logarithmic error (RMSLE) is a crucial performance metric for evaluating regression models, focusing on the logarithmic scale to compare the expected and actual values. As shown in Fig. 8(b), the error is initially large after approximately 10 epochs but decreases exponentially to below 0.2 as the number of iterations increases.



(a) Model metric rankings

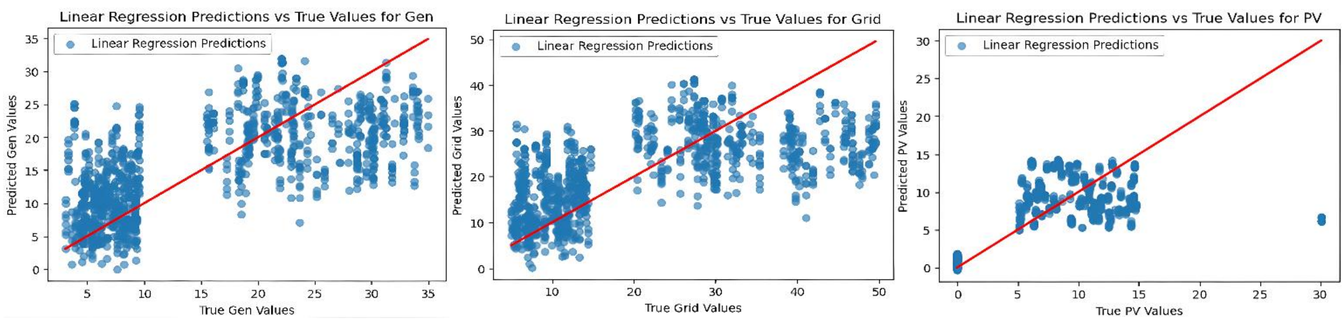


(b) ANN root means square error

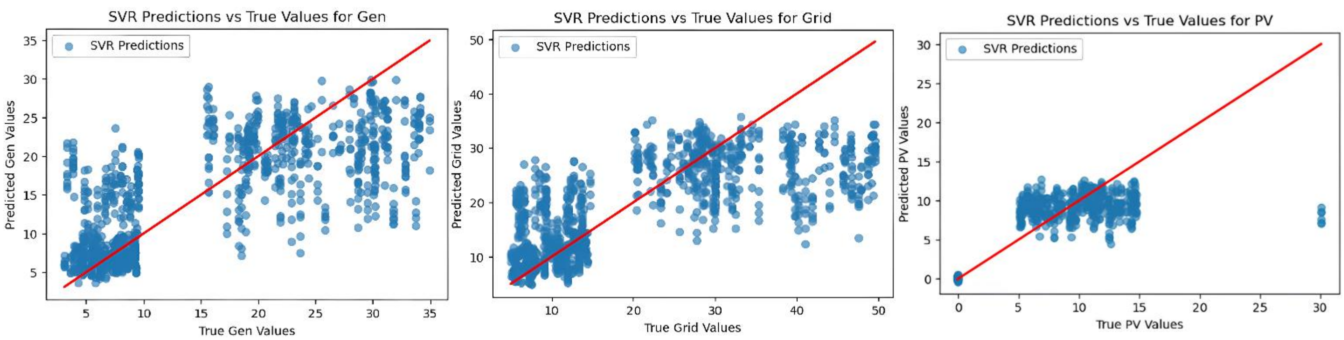
Fig. 8 Plot of model evaluation metrics

3.6. Model prediction analysis

This section analyzes scatter plots of predicted versus actual target outputs to assess model performance. The scatter plots in Fig. 9(a) show that the LR model exhibits significant scatter, indicating a poor fit. In Fig. 9(b), the SVR model demonstrates better clustering but still displays noticeable outliers. Fig. 9(c) illustrates that the XGBoost model achieves moderate fitting with significant scatter. In contrast, Fig. 9(d) shows that the ANN provides a better fit with minimal outliers, while in Fig. 9(e), the RF model also demonstrates improved clustering around the reference line.

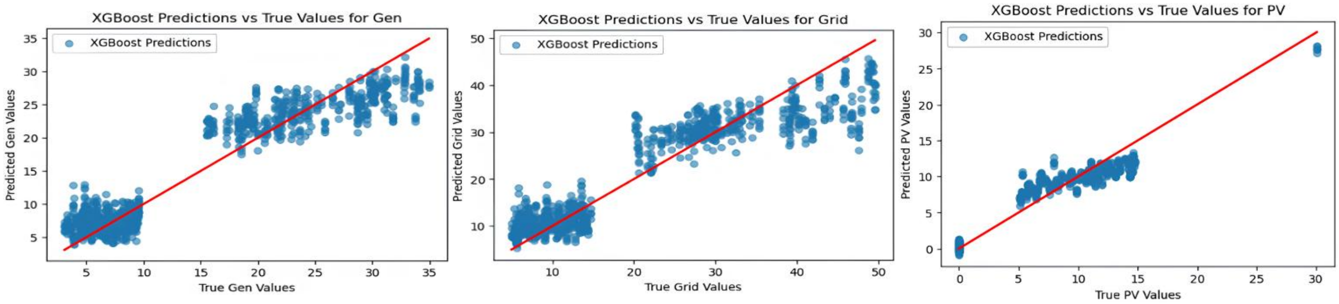


(a) Linear regression prediction output

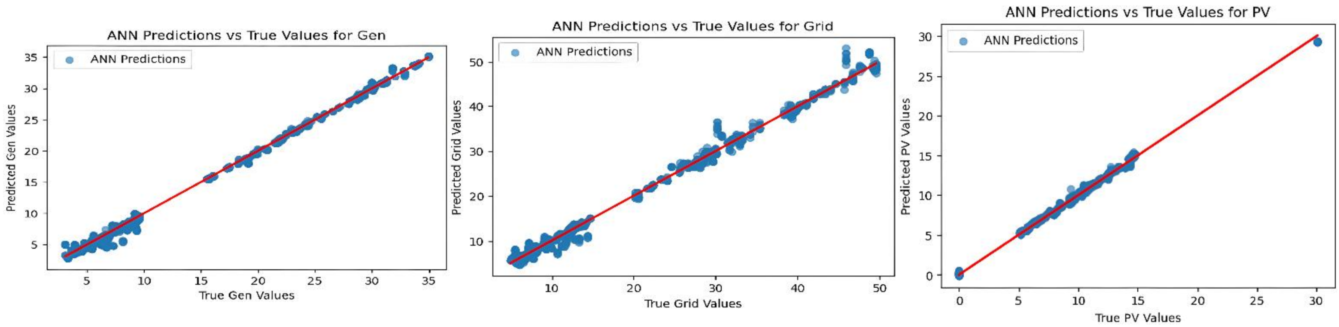


(b) SVR prediction output

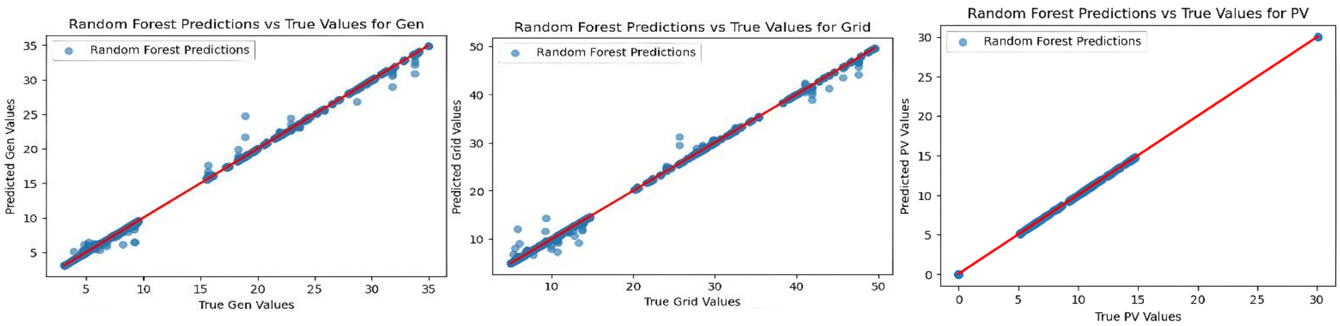
Fig. 9 Plot of proposed models' prediction



(c) XGBoost predictions outputs



(d) ANN predictions outputs



(e) Randon forest prediction outputs

Fig. 9 Plot of proposed models' prediction (continued)

4. Conclusion

In this study, machine learning models—LR, XGBoost, SVR, ANN, and RF—were developed for the multioutput forecast of the energy demand of a hybrid microgrid system. These models were optimized through hyperparameter tuning, aiming to enhance predictive accuracy and interpretability concerning the effects of weather parameters, holidays, and office hours on energy demand. The models were built using data from the Nile University of Nigeria's power station one energy source.

Furthermore, SHAP analysis revealed the positive impact of input predictors on predicted energy sources and their yields. Model performance was assessed using R^2, MAE, and MSE metrics, with the RF model showing superior results with an MSE of 0.2023, MAE of 0.0831, RMSE of 0.4498, and an R^2 score of 0.9992. This study contributes to the body of literature as follows.

(1) The study effectively developed machine learning models for multioutput prediction of the energy yield of a hybrid microgrid composed of diverse energy sources toward meeting load demand.

(2) This study addresses the challenge of predicting energy demand from hybrid microgrid systems comprising renewable energy demands using a random forest. Results show that the RF model outperforms other models in prediction and system performance.

(3) The proposed strategy was successfully implemented for energy demand forecasting at Nile University of Nigeria, Abuja.

Consequently, this study acknowledges the limitation in tuning hyperparameters in ML models; therefore, future research will consider hybridizing metaheuristic optimization algorithms with ML models for better hyperparameter tuning. Furthermore, the effect of energy yield on the fluctuations of voltage and frequency could be explored to enhance energy management systems. Finally, the proposed models can be adopted for energy systems with similar datasets.

Conflicts of Interest

The authors declare no conflict of interest.

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