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Dynamic Satin Bowerbird-Tuned XGBoost for Enhancing Energy Efficiency in IoT-Enabled Smart Grids

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The development of smart grid (SG) technologies has significantly transformed the energy industry, particularly with the explosive growth of the Internet of Things (IoT). SG's leverage IoT technologies to optimize electricity distribution, enhance operational efficiency, and improve energy management. However, challenges such as high energy consumption, security vulnerabilities, and limitations in real-time data processing hinder the full potential of IoT-enabled SGs. It explores the role of AI and ML in enhancing IoT-enabled SG systems to improve energy efficiency. The Dynamic Satin Bowerbird-tuned Extreme Gradient Boosting (DSB-XGBoost) algorithm is applied for short-term energy forecasting and optimizing energy efficiency in Python. AI-driven IoT sensors continuously collect data on power usage, voltage fluctuations, and demand patterns. To ensure data accuracy and consistency, data cleaning and Z-score normalization are employed for uniform data distribution. An AI-based system was used to enable real-time energy monitoring, efficient load balancing, and seamless communication between energy providers and consumers. Experimental findings demonstrate that the proposed system achieves a significant reduction in precision (91.5%), accuracy (90%), RMSE (0.17), MAE (0.12), and MSE (0.14) in energy forecasting compared to traditional methods. Furthermore, real-time AI optimization reduces power wastage, enhances energy efficiency, and lowers operational costs. These results highlight how AI and ML may transform SG systems by making them more flexible and effective, paving the way for sustainable, adaptive, and highly effective energy management systems.

Povzetek: AI-podprta pametna omrežja izboljšujejo napovedovanje porabe in učinkovitost energije ter zmanjšujejo izgube.

1 Introduction

Modern trends in energy consumption and sustainable power management created an essential need for SG development [1]. SGs represent advanced energy networks, which employ contemporary communication and information technology for enhancing electric power generation, distribution, and consumption. The IoT enables immediate monitoring, control, and automation of the entire power infrastructure, thereby greatly enhancing the efficiency and functionality of modern SGs [2]. Coupled with sensors, smart meters, communication networks, and data analytics, IoT-enabled SGs are a truly intelligent energy ecosystem that optimizes resource use, lowers operational costs, and enhances grid reliability. In SG, IoT components such as smart meters, load controllers, and automated switches continuously monitor energy flow performance within the electrical grid [3]. This data allows grid operators to detect inaccuracies in real-time and predict a demand pattern to respond better to eventual disruptions. Smart meters help establish connections that permit consumers to interact with utility providers and enable them to set prices according to usage patterns. The integration of solar and wind power by IoT-based systems provides a reliable power supply through their ability to stabilize renewable energy's variable nature [4].

The deployment of IoT within SG brings many advantages when it comes to energy efficiency and sustainability [5]. Real-time data collection and analysis allow precise control over the generation and distribution of energy so that wasteful energy is lost due to a lack of overall efficiency. IoT-enabled systems can automatically increase and decrease power generation and consumption according to real-time demand, thus avoiding overload and blackout. IoT facilitates the seamless integration of renewable energy sources by adjusting grid operations based on weather patterns and energy production levels. Smart meters and connected devices enable consumers to monitor their energy usage, adopt energy-saving behaviours, and participate in demand-side management programs. IoT-enabled SG systems promise to revolutionize energy management through increased efficiency, lower costs, and a higher ability to support the transition toward sustainable energy [6]. The continuous development of IoT technology will continue to propel smart-grid development forward, combined with a boost in data security and interoperability, ensuring that SG will be a core component of future energy infrastructures [7]. The limitations of IoT-enabled SG arise from security risks associated with data protection, technical incompatibilities, expensive implementation expenses, privacy threats to data ownership and security through networks, and complications with integrating mixed IoT equipment and renewable power sources. It discovers the role of AI and ML in enhancing IoT-enabled SG systems to improve energy efficiency. The DSB-XGBoost system is applied for short-term energy prediction and optimizing energy efficacy.

Motivation of the research

The motivation behind this research origin from the increasing complexity of managing energy demand in IoT-enabled smart grids, where traditional methods struggle with real-time adaptability, accuracy, and efficiency. With growing energy consumption, integrating AI-driven models like DSB-XGBoost offers a powerful solution for dynamic forecasting, minimizing energy waste, and enabling smarter, sustainable grid operations.

Key contributions

- Research introduced a novel AI-based solution to enhance prediction performance.
- Collected and utilized a relevant IoT smart grid dataset, containing real-time and historical energy data such as power consumption, voltage, and environmental factors.
- Applied comprehensive data preprocessing, including data cleaning and Z-score normalization, to ensure data consistency and improve model input quality.
- Implemented logistic chaos and Cauchy variation in DSB to optimize hyperparameters dynamically, improving convergence speed and solution quality.
- Trained and evaluated the DSB-XGBoost model, showing improved performance metrics (accuracy, precision, RMSE, MAE, MSE) over traditional models.

2 Related work

Awan et al. [8] suggested a PSO-based execute-before-after dependency model as a method to raise the energy demand optimization of smart grids to balance demand needs for end-users and utilities, via a two-phase machine learning model. Based on the simulation results, the research produced an algorithm that improved demand scheduling and load management. However, the approach was not responsive to changes in dynamic environments, had no ability for real-time learning, and was not designed for hyperparameter tuning, which limits the model performance in a continually evolving grid infrastructure that needs optimization and intelligent responses to changing demand needs.

Minh et al. [9] performed a study of a method utilizing edge computing to increase data processing within IoT-enabled smart grids. The method improved latency and allowed for distributed processing and local decisions made at the edge of the grid. Although the framework locally offered better grid responsiveness than the standard grid, machine learning was not included in this method. Without some level of adaptive intelligence, the method unsuccessfully increased the capacity of the smart grid to account for real-time energy forecasting or complex load changes affecting the smart grid.

Sheela et al. [10] established a smart energy meter that includes voltage and current sensors, plus Wi-Fi to monitor domestic energy use. The goal of this effort was to enable real-time monitoring with the capability to upload data to the cloud for residential power usage. While the system performed well in collecting energy data, there were no intelligent algorithms or forecasting capabilities. Without machine learning, the work is just passive measurement without the capacity to improve energy management or decision-making in smart grid systems. The remaining related works are presented in Table 1.

Table 1: Summary of recent AI and IoT approaches for energy optimization in smart grids

Ref.	Area Focused	Algorithms / Techniques	Performance / Key Results	Limitations
Natarajan et al. [11]	Smart building energy prediction	CNN–LSTM hybrid deep model	Accurate energy forecasts; supports sustainable planning	Computationally intensive, large data requirement, inflexible to real-time changes

Jose and Mathew [12]	IoT-based KPI model for process manufacturing (cement plant)	IoT data acquisition, ERP integration, AI/ML, KPI dashboards, two-way control	Validated plant- and head-office KPIs; enabled continuous monitoring and control	Proof in a single industry only; scalability across industries is untested
Khudor et al. [13]	Multitask energy optimization across buildings	RegClassXNet (EfficientNet + Xception + Swin-Transformer), PDCA, attribute hybridization	R^2=95%, MAE=2.1, RMSE=1.8; outperformed CNN, LSTM, RF; included stability metrics (LVCI, TPSM, OCC)	High computational demand; less accessible in resource-limited settings
Zhang et al. [14]	Smart grid situational awareness & fault warning	Digital twin platform, static/dynamic indicators, LSTM model	Accuracy 98.72%, Recall 98.95%, F1 = 99.06%, Fault warning = 99.82%, Response time = 0.083 s	Dependent on specific data infrastructure; limited tested scalability
Zhang [15]	Dynamic model selection for energy plant forecasting (Informatica, 2025)	Energy Guard Ensemble Selector (EGES): RF, SVM, GBM, KNN, Logistic Regression	The research achieves higher Accuracy, Precision, and Recall scores	Increased complexity; dynamic model handling may raise implementation overhead

Research gap

Researches do not sufficiently address uncertain cybersecurity challenges and the adoption of AI-based optimization, which detracts from acceptance in dynamic and large-scale, security-centric smart grid environments. The energy management system is limited to older buildings, thus may not generalize to current infrastructure. It is not focused on scaling air handling systems, real-time data processing, and effective adoption of AI-based techniques, and highlights little to no security and broad interoperability related to the smart grid ecosystem. This research overcomes prior limitations by integrating the novel DSB-XGBoost algorithm, enabling real-time energy forecasting, adaptive load balancing, and enhanced scalability. Unlike earlier models, it ensures higher accuracy, reduced error rates, and improved optimization. The method's uniqueness lies in its dynamic tuning and AI-driven responsiveness to changing grid conditions.

3 Methodology

The objective of this research is to enhance energy efficiency in IoT-enabled smart grids through accurate real-time forecasting and adaptive optimization. The methodology uses IoT sensors to collect energy and environmental data, followed by data cleaning and Z-score normalization. A Dynamic Satin Bowerbird (DSB) algorithm optimizes XGBoost hyperparameters via logistic chaos initialization and Cauchy variation. The tuned DSB-XGBoost model forecasts energy demand, enabling efficient load balancing, reduced power wastage, and improved grid performance. Figure 1 shows the step-by-step process of the methodology flow.

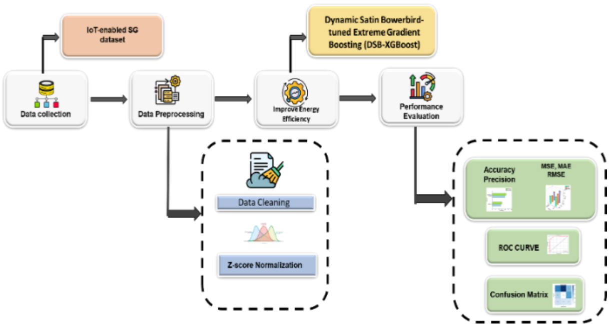

Figure 1: Schematic diagram of proposed framework

3.1 Data collection

The IoT-enabled SG dataset was gathered from a Kaggle source-https://www.kaggle.com/datasets/ziya07/iot-enabled-smart-grid-dataset/data. This dataset is intended for use in IoT-enabled smart grids for AI and ML-based energy efficiency improvement. Power consumption, voltage, current, grid frequency, reactive and active power, renewable energy generation, and environmental variables are all covered, both in real time and in the past. Using AI-driven predictive analytics, the dataset facilitates anomaly detection, load balancing, and energy forecasting. Based on demand response events, integration of renewable energy sources, and consumption patterns, the goal variable, Energy_Efficiency_Score, measures the total efficiency of power utilization. Research on AI-driven IoT applications, sustainable energy management, and smart grid optimization can benefit greatly from this dataset.

3.2 Data preprocessing

Z-score normalization serves as the required data preprocessing method for IoT-enabled SG systems to standardize the energy consumption alongside sensor data and noise removal. The data transformation method through mean subtraction and standard deviation division creates a uniform distribution, which promotes precise analysis and efficiency optimizations for SG power operations. Data cleaning removes corrupted or irrelevant data that appears in sensor measurements and sends information.

3.2.1 Data cleaning

The initial step for cleaning IoT-enabled SG data requires addressing missing values either by replacement or deletion to minimum extent. Data clean-up requires duplicate removal to eliminate data duplication. To improve model performance, normalization techniques should be applied to numerical values together with standardization of units to create consistent measures. Cartesian variables should be converted to numbers through one-hot encoding or label encoding techniques. The data should be formatted correctly for date-times, followed by the extraction of useful features that include hour time, day identifier, and seasonal indicators. Data drift should be handled through the alignment of historical data and real-time data. The final step should check that features have complete, consistent data to guarantee precise model development.

3.2.2 Z-Score normalization

Z-score normalization in IoT-enabled SG networks standardizes energy data, enhancing anomaly identification, eliminating noise, and maximizing energy efficiency through precise measurements. To transform all data with different scales to the default scale, it normalizes the set of data to the previously indicated scale. This is particularly effective for energy data in smart grids, where sensor readings (e.g., voltage, current, load) often vary widely in scale. Z-score normalization is determined by Equation (1).

$$z\_score = \frac{(w-\mu)}{\sigma} \tag{1}$$

3.3 Improve energy efficiency using dynamic satin bowerbird-tuned extreme gradient boosting (DSB-XGBoost)

The proposed method combines XGBoost with Dynamic Satin Bowerbird (DSB) optimization to provide a reliable, real-time energy forecasting model designed for smart grid systems enabled by the Internet of Things. In contrast to traditional models, which either lack dynamic parameter tweaking or demand a lot of processing power, DSB-XGBoost uses Cauchy variation and logistic chaos initialization to adaptively optimize hyperparameters. This guarantees enhanced prediction accuracy, decreased overfitting, and quicker convergence even with highly changeable smart grid data.

3.3.1 XGBoost

Gradient Boost is computationally expensive and slow to train, especially with large datasets. It is also prone to overfitting if hyperparameters are not carefully tuned. So, this research utilized XGBoost since it has been historically shown to be productive in making predictions from large, complex datasets while accurately maintaining the values of the predicted output. It utilizes regularization to reduce the likelihood of overfitting, can run in parallel, which decreases the integration time, and is effective for both classification and regression tasks. Due to its robustness, scalability, and ability to handle various types of relevant features, it is well-suited for real-time energy forecasting in IoT-connected smart grids. Until the highest level of precision is achieved, the same procedure is repeated. The following is a summary of the entire workflow. Let's consider the input information DS, which Equation (2) represents.

$$DS = a; d, \quad |DS| = m \quad a \in Q^n, \; d \in Q \tag{2}$$

Where a represents the feature set of the IoT smart grid (i.e., voltage, current, temperature), while d is the target variable - the predicted energy demand. For clarity purposes, m is the total number of instances in time we recorded, while n is the number of measured structures used for prediction optimization. Equation (3) is used to determine the total of the expected scores in l trees.

$$\widehat{d_j} = \sum_{l=1}^{L} e_l(a_j), \quad e_l \in E \tag{3}$$

Where a_j denotes the jth instance of the training set and $\widehat{d_j}$ denotes the occurrence in the lth boost. All decision tree values are represented by E, and the value of the lth tree is denoted by $e_l(a_j)$. Using Equation (4), the XGBoost lowers the loss function K_l.

$$K_l = \sum_{j=1}^{m} K(\widehat{d_j}, d_j) \tag{4}$$

This research aims to improve energy forecasting for IoT-enabled smart grids. As such, K_l represents for the l-th boosting iteration, the whole loss function. The K quantifies the difference between the predicted energy demand hat d_j and the actual demand $\widehat{d_j}$ to provide information for the model to minimize forecasting loss. Equation (5) provides XGBoost's Objective Function (OF).

$$OF = \sum_{j=1}^{m} K\left(\widehat{d_j}, d_j\right) + \sum_{j=1}^{l} Q(e_j) \tag{5}$$

Here, $\widehat{d_j}$ stands for the predicted label, d_j for the actual label, and K for the loss function. The training tree's pursuing computing function is shown by $Q(e)$. Equation (6) provides the three functions $e(a)$, which it constructs first to define the complexity.

$$e(a) = x_r(a), \qquad x \in Q^K \rightarrow \{1,2, \ldots K\} \tag{6}$$

Improving energy forecasting in IoT-connected smart grids, r maps the particular data instance to a decision tree leaf, while x is the predicted score for that leaf. The K is the number of leaves, which directly relates to the complexity of the model and the accuracy Q^K of the forecast. Equation (7) provides the calculation complexity of the penalized model.

$$Q(e) = \gamma \times K + \alpha\left(\left||x|\right|\right) + \frac{1}{2} \times \lambda \times \left||x|\right|^2 \tag{7}$$

Each leaf's value is denoted by γ, where λ as well as γ are fixed values. The tree's weight value is indicated by $\left||x|\right|$. By using an additive model, the XGBoost compares the curve tree output to the previous tree result. Equation (8) provides the OF, which is determined at the sth step.

$$OF^{(S)} = \sum_{j=1}^{m} K(d_j, \hat{d}_j^{s}) + e_s\left(a_j\right) + Q(e_s) + d \tag{8}$$

In the above equation, d is a constant, and e_s denotes objective function reduction. Additionally, it calculates the second-order Taylor series, which is provided in Equations (9) to (11), which calculates h_j and g_j.

$$OF^{(S)} = \sum_{j=1}^{m} \left[K\left(d_j, \hat{d}_j^{s-1}\right) + h_j \times e_s\left(a_j\right) + \frac{1}{2} \times g_j e_s^2\left(a_j\right)\right] + Q(e_s) + d \tag{9}$$

$$h_j = \partial_{\hat{d}_j^{s-1}} K\left(d_j, \hat{d}_j^{s-1}\right) \tag{10}$$

$$g_j = \partial^2{}_{\hat{d}_j^{s-1}} K\left(d_j, \hat{d}_j^{s-1}\right) \tag{11}$$

The above equations give the second-order Taylor expansion for the objective function that is used in XGBoost, where h_j and g_j are the loss function. These supports optimize energy forecasting because they identify the loss parameter values to minimize the prediction errors in smart grid systems. The regularization factor from Equation (7-12) is used to eliminate the constant.

$$OF^{(S)} = \sum_{j=1}^{m} \left[h_j \times e_s\left(a_j\right) + \frac{1}{2} \times g_j e_s^2\left(a_j\right)\right] + \gamma^s + \alpha \times \sum_{i=1}^{S} x_j^2 \tag{12}$$

The equation shows the Objective Function (OF) in your DSB-XGBoost model. The objective function consists of the model's prediction loss and regularization terms (γ and α) to keep predictions accurate and the model's complexity limited. The function that has balanced predictive power for your model to limit model complexity likely estimates the potential for optimal energy forecasting focused on minimizing the error while controlling the smart grid predictions' ability to overfit.

3.3.2 DSB

The DSB algorithm is a nature-inspired optimization technique that emulates the mating approach of Satin Bowerbirds to return an optimal solution. The DSB algorithm dynamically tunes hyperparameters of XGBoost, while predicting energy based on load, to improve forecasting accuracy and efficiency. With improvement to convergence speed and reduction of overfitting, the DSB algorithm enables better and more adaptive energy management in an IoT-enabled smart grid.

- **Logistic Chaos's initialization**

A better initialization technique will significantly speed up the intelligent optimization algorithm's convergence speed, even though the initial population of the algorithm uses a random initialization mode per natural law. This depends on the engineering applications and convergence speed requirements. Additionally, the SB initializes the population using random values. A logistic chaos map was developed to increase the beginning population's variety, which in turn produced a better starting population, which in turn increased the algorithm's convergence speed and optimization accuracy. Equation (13) illustrates the logistic chaos map calculating method.

$$W_{j+1} = \mu W_j * \left(1 - W_j\right) \tag{13}$$

Optimizing IoT-enabled smart grid forecasting, the control parameter μ when initializing logistic chaos defines the diversity of the initial population. Proposing the use of $\mu = 4$ maximizes the level of chaos and favours exploration, enabling DSB-XGBoost to identify optimal hyperparameters that facilitate a successful, accurate, and efficient method of energy prediction. Consequently, it set several μ at 4. Equation (14) is used as the population initialization.

$$pop(j).Position = Y(j,:).* (VarMax - VarMin) + VarMin \quad (14)$$

➢ **The Cauchy variation approach**

The Cauchy mutation approach is used instead of the traditional SB mutation method, which ensures more disruption close to the existing population by producing a longer distribution in the remainder and a short peak distributed at the origin. Equation (15) shows the Cauchy variation approach.

$$W_{j,i}^{s+1} = W_{best} + Cauchy(0,1) \oplus W_{best}(s) \quad (15)$$

Within the context of this study, $W_{j,i}^{s+1}$ identifies the one set of XGBoost hyperparameters at iteration s that should be optimized further. The $Cauchy(0,1)$ distribution incorporates structured randomness into $W_{best}(s)$, to search for new values of hyperparameters, thus enabling optimal energy forecasting for IoT-enabled smart grids. Equation (16) computes the relevant variation probability.

$$O_t = -\exp\left(1 - \frac{it}{MaxIt}\right)^{20} + o \quad (16)$$

In optimizing the forecasting methods for IoT-enabled smart grids, $MaxIt$ represents the total number of iterations of the algorithm, and is the control parameter when optimizing to depth; O_t indicates the threshold for mutation acceptance. A Cauchy mutation only occurs if the associated probability condition is fulfilled. This enables the maximum parameter values to be fine-tuned for an optimal energy prediction reflex. Algorithm 1 shows the process of DSB-XGBoost.

Algorithm 1: The Dynamic Satin Bowerbird-tuned Extreme Gradient Boosting (DSB-XGBoost)

Step 1: Initialize XGBoost
Set learning_rate = random between 0.01 and 0.3
Set max_depth = random between 3 and 10
Set subsample = random between 0.5 and 1
Set colsample_bytree = random between 0.5 and 1
Step 2: Initialize DSB
For i = 1 to population_size:
W[i] = random between 0 and 1
W[i] = $\mu \times W[i] \times (1 - W[i])$
Map W[i] to XGBoost parameters
Step 3: DSB-XGBoost Optimization
For t = 1 to max_iterations:
For i = 1 to population_size:
Train XGBoost with W[i]'s parameters
Evaluate fitness_i (e.g., RMSE)
Find W_best with the lowest RMSE
For i = 1 to population_size:
Generate random q ∈ [0, 1]
If q < mutation_probability:
W_new = W_best + $Cauchy$ (0,1)
If q < O_t:
W[i] = W_new
Else:
W[i] = W[i]
Else:
W[i] = W[i]
END IF

❋ **Parameter setup**

Hyperparameters for the DSB-XGBoost method are described in Table 2.

Table 2: Parameter Setup

Hyperparameters	Typical Values
Max depth (max depth)	3, 5, 10
Subsample ratio (subsample)	0.5, 0.7, 1.0
Column sample by tree	0.5, 0.8, 1.0
Number of estimators	100, 200, 300
Mutation probability (μ)	0.1, 0.2, 0.3
Logistic chaos control (μ_val)	3.9, 4.0
Regularization alpha (α)	0.1, 0.2
Regularization gamma (γ)	0.1, 0.3
Fitness metric	RMSE, MAE

4 Result and discussion

AI-driven short-term energy forecasting and optimization with the DSB-XGBoost algorithm to improve energy efficiency in IoT-enabled smart grids. The experimental setup consists of Python 3.12 operating on Windows 11 with a 7th-generation Core i7 processor and 32 GB of RAM. This contemporary laptop design greatly facilitated multitasking, development tasks, and demanding performance assessments. The proposed framework, DSB-XGBoost, is compared with the conventional models, including Gated Recurrent Unit (GRU) [16] and Particle Swarm Optimization-Smart Grid (PSO-SG) [17], using result comparison metrics, including precision, accuracy, RMSE, MAE, and MSE. The performance comparison of the suggested and conventional approaches is displayed in Table 3.

Table 3: Overall Result of RMSE, MAE, MSE, Precision, and Accuracy

Method	**Accuracy**	**Precision**	**RMSE**	**MSE**	**MAE**
GRU [16]	-	-	0.22	0.17	0.19
PSO-SG [17]	83%	85%	-	-	-
DSB-XGBoost [Proposed]	90%	91.5%	0.17	0.14	0.12

4.1 Correlation matrix

By calculating the pairwise correlation coefficients between several variables, a correlation matrix measures the relationships between them. It shows how demand patterns, voltage swings, and power consumption interact in the context of smart grids, directing AI algorithms to enhance energy forecasting and maximize system efficiency. Figure 2 Outcome of correlation analysis.

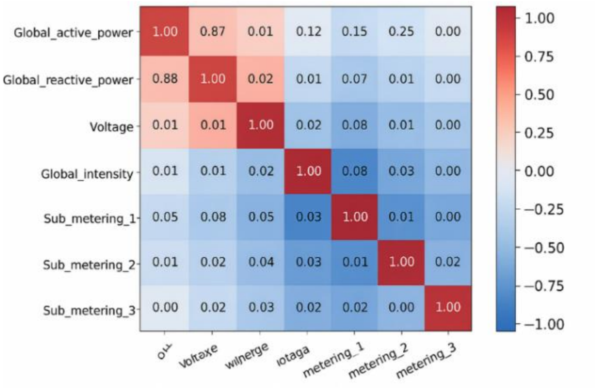

Figure 2: Variable relationships from correlation analysis

The Global_active_power and Global_reactive_power have a high correlation (0.88), according to the correlation heatmap, meaning that changes in one have a significant impact on the other. Most factors have little association with voltage, indicating that it stays mostly constant. Weak correlations between sub-metering variables indicate different localized consumption patterns. These associations are essential for the DSB-XGBoost model in our AI-driven IoT-enabled smart grid since detecting highly correlated characteristics increases forecasting accuracy, facilitates effective load balancing, and improves overall energy management for adaptive and sustainable smart grid operations.

4.1.1 Confusion matrix

The effectiveness of a classification algorithm forecasting energy efficiency levels in an IoT-enabled smart grid is displayed in this confusion matrix. Columns show anticipated labels, and rows show genuine labels. High off-diagonal values suggest misclassifications, indicating the model struggles to distinguish between certain efficiency states, highlighting the need for feature tuning or improved model complexity. Figure 3 presents the result of the confusion matrix.

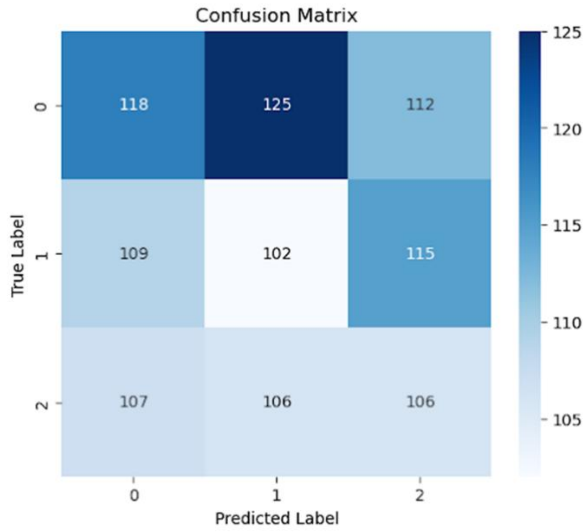

Figure 3: Confusion matrix outcomes

The model's classification accuracy is displayed in this confusion matrix, which illustrates how well it matched expected and actual energy efficiency levels. The overwhelming diagonal bias demonstrates that DSB-XGBoost can accurately identify most efficiency levels and that misclassification is minimal. This shows that the model is capable of managing complex energy-use patterns in IoT-enabled smart grids. The result reinforces the model's robustness in real-time deployment, when accurate recognition of energy states is critical to appropriate energy distribution and grid stabilization.

4.2 ROC curve

This ROC curve evaluates the performance of an AI model for energy efficiency in IoT-enabled SG. The high AUC value (0.97) indicates strong predictive accuracy in distinguishing efficient from inefficient states based on power usage, demand response, and renewable integration, supporting better load balancing and anomaly detection. Figure 4 displays the findings of the ROC.

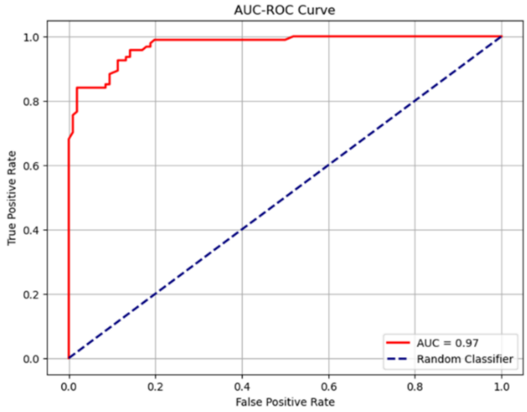

Figure 4: ROC Curve outcomes

The ROC curve demonstrates the true positive rate and false positive rate at several thresholds. The AUC score of 0.97 reveals this model's exemplary ability to classify energy states that were efficient and inefficient. Higher separability indicates that DSB-XGBoost can classify usage patterns reliably, even under variable grid conditions. It also confirms DSB-XGBoost's capability to assist demand response, decrease power loss, and improve energy optimization through very accurate real-time forecasts.

4.3 Accuracy

IoT-enabled smart grid systems' energy efficiency accuracy depends on their ability to accurately forecast energy effectiveness scores and optimize grid performance to reduce prediction mistakes. The suggested DSB-XGBoost method attains an accuracy of 90%, significantly outperforming the traditional technique PSO-SG, which achieved 83%, respectively.

4.4 Precision

The exact measuring capabilities of IoT-enabled SG help organizations determine energy-efficient and inefficient areas by offering precision performance measurements. The proposed DSB-XGBoost model outperforms traditional energy optimization approaches with a precision of 91.5%, while the PSO-SG models have a lower precision of 85%, respectively; DSB-XGBoost proves efficiency in predicting energy demand as well as performing load balancing functions that enhance grid efficiency. Figure 5 displays the results of precision and accuracy.

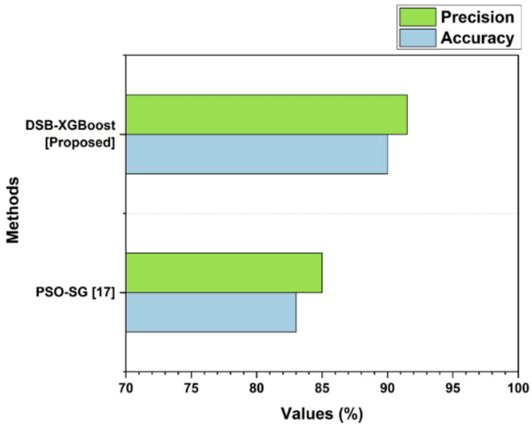

Figure 5: Graphical representation of accuracy and precision results

The graph compares the precision and accuracy of DSB-XGBoost against standard models, including PSO-SG. DSB-XGBoost processed and predicted the ongoing energy demand with superior performance at 91.5% precision and 90% accuracy. The use of precision and accuracy indicates the reliability and ability of DSB-XGBoost to use intelligent energy distribution (reduce inefficiencies), while also demonstrating its capability in obtaining information and responding in real-time towards the changing dynamic smart grid demands.

4.5 MAE

MAE determines the average absolute variations between predicted and actual scores from the IoT-enabled smart grid energy efficiency model. A system achieves better prediction performance when its MAE value decreases. The proposed AI-driven predictive model using a DSB-XGBoost approach attains an MAE value of 0.12 in energy efficiency prediction, while the traditional GRU approach yields a higher MAE value of 0.19, respectively. The proposed model proves effective for enhancing energy efficiency and enabling the sustainable operation of SG.

4.6 MSE

The MSE for the IoT-powered smart grid energy efficiency model assigns numerical values to the average squared distances between forecasted and actual energy efficiency measurements. The MSE evaluates prediction errors in a complete manner, as lower values show superior model performance. The proposed AI-based model DSB-XGBoost reaches an MSE value of 0.14, whereas the traditional method, GRU, results in a higher MSE value of 0.17, respectively.

4.7 RMSE

The RMSE value for the IoT-enabled smart grid energy efficiency model defines the actual energy efficiency ratings. The RMSE establishes prediction accuracy by showing clear precision while minimizing the value to indicate superior model achievement. The proposed AI-based DSB-XGBoost model achieves an RMSE value of 0.17, whereas the traditional method, GRU, results in a higher RMSE value of 0.22. Figure 6 presents the outcomes of MAE, MSE, and RMSE.

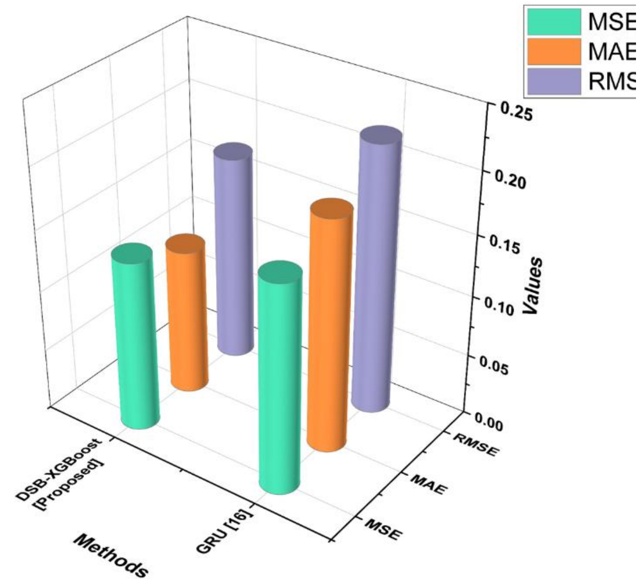

Figure 6: Graphical Representation of RMSE, MAE, and MSE Outcomes

The above graph provides a visualization of error metrics (RMSE, MAE, MSE) for DSB-XGBoost against benchmark models. The lower the values for all three errors affirm that the proposed model is providing more reliable energy consumption forecasts. The lesser values of RMSE (0.17), MAE (0.12), and MSE (0.14) indicate greater stability in learning and predicting the energy load with precision. Improved accuracy and stability are especially important for smart grid applications, as they enable improved decision-making, effectively balancing load among energy resources, and productively planning energy resources across a highly dynamic IoT-based energy system.

Dataset comparison

The proposed DSB-XGBoost model is trained on Real-Time Smart Grid Energy Dataset [18] and IoT-Enabled Smart Grid Dataset. The goal of this comparative evaluation was to determine the model's generalization ability in both real-time and recorded smart grid conditions. The model's performance was measured using standard forecasting metrics: RMSE, MAE, MSE, precision, and accuracy. DSB-XGBoost consistently produced accurate forecasts for both datasets with marginally better results on the real-time dataset. While marginal, the improvement could be significant, as the model can adjust to dynamic and constantly changing grid conditions. Table 4 shows the viability of the proposed model being deployed in operating smart grid systems, where minor improvements in predictive power would lead to vast improvements in energy efficiency and costs.

Table 4: Model performance comparison between proposed and real-time smart grid datasets

Metrics	IoT-Enabled Smart Grid Dataset [Proposed]	Real-Time Smart Grid Energy Dataset [18]
Accuracy	**91.50**	90.00
Precision	**92.10**	91.50
RMSE	**0.15**	0.17
MAE	**0.11**	0.12
MSE	**0.13**	0.14

The table shows a comparison between the proposed Enabled Smart Grid Dataset and the Real-Time Smart Grid Energy Dataset [18]. The proposed dataset achieves better precision and accuracy with lower RMSE, MAE, and MSE values, which means it outperforms the Real-Time Smart Grid Energy Dataset and is a more reliable predictor for energy forecasting in IoT-enabled smart grid applications.

5 Discussion

IoT-enabled smart grid systems enhance energy efficiency by integrating immediate monitoring, predictive analysis, and automatic control, optimizing power usage, balancing loads, and improving renewable energy integration. GRU [16] models in SG struggle with long-term dependencies, vanishing gradients, and high computational costs, limiting real-time responsiveness. It may also underperform with irregular energy patterns and noisy IoT data. PSO-SG [17] methods face challenges with convergence speed, getting trapped in local optima, and high sensitivity to parameter tuning, reducing adaptability to dynamic grid conditions. Both methods may lack scalability and robustness in handling complex, multi-modal data from IoT devices, limiting accuracy and efficiency in real-time energy management. The proposed DSB-XGBoost method enhances smart grid efficiency by combining XGBoost's high predictive accuracy with DSB optimization for improved parameter tuning. It overcomes GRU's dependency and noise issues with better feature selection and handles PSO-SG's convergence problems by dynamically adjusting search strategies, ensuring faster, more accurate, and scalable real-time energy management.

6 Conclusion

Energy consumption and operational efficiency have significantly improved due to the use of AI and ML in IoT-enabled SG. AI-driven IoT sensors collected real-time data on power usage, voltage fluctuations, and demand patterns, providing a comprehensive foundation for analysis. Data pretreatment methods, such as Z-score normalization and data cleaning, ensured data accuracy and consistency for uniform data distribution. The proposed DSB-XGBoost algorithm enhanced short-term energy forecasting and real-time optimization, improving load balancing and energy management. Experimental results demonstrated a significant reduction in precision (91.5%), accuracy (90%), RMSE (0.17), MAE (0.12), and MSE (0.14), resulting in improved energy forecasting accuracy, reduced power wastage, and lower operational costs. In the dataset comparison, the proposed model outperforms the Real-Time Smart Grid dataset with higher accuracy and precision, and lower error rates, demonstrating more reliable energy forecasting. These results highlight how AI and ML may transform SG systems by making them more flexible and effective. The DSB-XGBoost algorithm's computational cost and reliance on dataset quality are limitations that can impact real-time scalability. To further increase energy forecasting accuracy and smart grid adaptability and enable wider application in dynamic and large-scale energy systems, future research might concentrate on integrating more diversified datasets, improving algorithm efficiency, and investigating hybrid AI models.

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Appendix

smart grid	SG	Edge Computing	EC
Root Mean Squared Error	RMSE	Deep Learning-enhanced Predictive Energy Modeling	DL-PEM
Mean Absolute Error	MAE	dynamic multi-hop	HDM
Mean Squared Error	MSE	low energy adaptive clustering hierarchy	LEACH
particle swarm optimization	PSO	Artificial Intelligence	AI
wireless sensor networks	WSN	Machine Learning	ML
sensor nodes	SN	Current and Voltage Sensors	CVS
Convolutional neural network-Long Short-term Memory	CNN-LSTM		