Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

JOURNAL OF STATISTICAL SCIENCES & DATA ANALYTICS
Department of Statistics, Ahmadu Bello University, Zaria, Nigeria | www.jossda.abu.edu.ng www.jossda.com.ng

Smart Grid Energy Management Using IoT and Machine Learning

M. J. Yeldu[1] and Y. G. Gelwasa[2]
[1]*Department of Computer Science, Abdullahi Fodio University of Science and Technology, Aliero, Nigerian*
[2]*Department of Electrical and Electronic Engineering, Abdullahi Fodio University of Science and Technology, Aliero, Nigeria*

Corresponding Author: mubarakjibril59@gmail.com
ORCID ID: 0009-0000-9158-5267

Corresponding Author:
M. J. Yeldu, Department of Computer Science, Abdullahi Fodio University of Science and Technology, Aliero, Nigeria. mubarakjibril59@gmail.com | ORCID ID: 0009-0000-9158-5267

Abstract

The increasing complexity of modern power systems due to growing electricity demand, renewable energy integration, distributed generation, and changing consumer behaviour has created the need for intelligent energy management solutions capable of achieving efficient, reliable, and sustainable grid operation. Conventional energy management approaches are increasingly challenged by the dynamic and uncertain characteristics of contemporary power networks, necessitating advanced technologies that can provide real-time monitoring, accurate prediction, and autonomous decision-making. This paper presents a comprehensive investigation of Smart Grid Energy Management Using IoT and Machine Learning, focusing on the integration of Internet of Things (IoT) technologies and machine learning (ML) algorithms for improving energy efficiency, grid reliability, and operational intelligence. The IoT infrastructure enables real-time acquisition of critical grid information through smart meters, intelligent electronic devices, sensors, and communication networks, providing large-scale heterogeneous datasets related to electricity consumption, voltage variation, frequency behaviour, renewable energy generation, and equipment conditions. Machine learning techniques are employed to analyse these data for applications including load forecasting, renewable energy prediction, demand response optimisation, fault detection, predictive maintenance, energy scheduling, and adaptive grid control. Advanced learning approaches such as artificial neural networks, deep learning, long short-term memory networks, support vector machines, and reinforcement learning are examined for their effectiveness in addressing complex energy management challenges. Recent developments in edge intelligence, federated learning, and privacy-preserving machine learning are further explored as emerging solutions for improving computational efficiency, data security, and real-time decision-making in IoT-driven smart grids. Despite the significant benefits of IoT and ML integration, challenges related to cybersecurity, data privacy, interoperability, communication latency, computational limitations, and model interpretability remain critical barriers to widespread implementation. This study highlights that the combination of IoT-enabled sensing and machine learning-based intelligence provides a transformative approach for developing adaptive, resilient, and sustainable smart grid energy management systems capable of supporting future decentralised and renewable-dominated power networks.

Keywords: Smart grid; Energy management; Internet of Things; Machine learning; Renewable energy; Demand response; Artificial intelligence

1. Introduction

The increasing demand for electrical energy, rapid urbanisation, integration of renewable energy resources, and growing complexity of modern power systems have accelerated the transition from conventional electrical networks to intelligent smart grid environments. Traditional power grids were mainly designed for centralised electricity generation and one-way energy delivery, making them less effective in handling the uncertainties associated with distributed generation, variable renewable energy sources, electric vehicles, and dynamic consumer behaviour. Smart grids provide a transformative solution by integrating advanced sensing, communication, automation, and computational intelligence technologies to enhance the efficiency, reliability, sustainability, and resilience of power systems (Gungor et al., 2023). Energy management has become a critical component of smart grid operation due to the need for optimal coordination between electricity generation, distribution, storage, and consumption. Effective energy management systems are required to achieve real-time monitoring, accurate load forecasting, efficient demand response, reduction of transmission and distribution losses, and improved utilisation of renewable energy resources. However, the unpredictable nature of renewable energy generation and variations in consumer electricity demand create significant challenges for conventional energy management techniques. Therefore, intelligent approaches capable of analysing large-scale energy data and making adaptive decisions are increasingly required for future power systems (Liu et al., 2024).

The Internet of Things (IoT) has emerged as a key enabling technology for smart grid energy management by providing a connected environment for real-time data acquisition and communication among power system components. IoT-based smart grids utilise smart meters, intelligent electronic devices, wireless sensor networks, and communication technologies to collect operational information from generation units, transmission systems, distribution networks, and end-users. These interconnected devices enable continuous monitoring of important electrical parameters such as voltage, current, frequency, power consumption, renewable energy output, and equipment status. Consequently, IoT improves grid visibility and provides the data infrastructure required for intelligent energy management applications (Al-Turjman et al., 2023). The massive volume of heterogeneous data generated by IoT-based smart grids requires advanced analytical methods capable of extracting useful information and supporting autonomous decision-making. Machine learning (ML) has gained significant attention as an effective approach for processing complex energy datasets and identifying hidden patterns within power system operations. Unlike conventional mathematical models that depend on fixed assumptions, machine learning algorithms can learn from historical and real-time data, enabling improved prediction, optimisation, and control of energy systems. Machine learning applications in smart grid energy management include electricity demand forecasting, renewable energy prediction, fault detection, energy scheduling, consumer behaviour analysis, and real-time grid optimisation (Zhang et al., 2023).

Several machine learning techniques have demonstrated promising performance in smart grid energy management. Artificial neural networks (ANNs) have been widely adopted for electricity load prediction due to their ability to model nonlinear relationships between energy consumption and influencing factors. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have further improved forecasting accuracy by effectively capturing temporal dependencies in electricity consumption and renewable energy generation patterns (Wang et al., 2024). These predictive capabilities enable utility operators to make informed decisions regarding generation scheduling, energy storage management, and demand-side control. Furthermore, reinforcement learning (RL) has emerged as an advanced machine learning approach for autonomous energy management in smart grids. Reinforcement learning algorithms allow intelligent agents to learn optimal control strategies through continuous interaction with the energy environment. This capability makes RL suitable for applications such as microgrid energy optimisation, battery energy storage management, demand response coordination, and real-time electricity pricing. Recent studies have demonstrated that reinforcement learning-based approaches can improve energy efficiency by dynamically adapting to changing grid conditions (Kong et al., 2023).

The combination of IoT and machine learning provides significant advantages for smart grid energy management by integrating real-time sensing capabilities with intelligent decision-making. IoT provides the necessary infrastructure for collecting large-scale operational data, while machine learning transforms these data into meaningful insights for prediction, optimisation, and automated control. This integration supports improved renewable energy integration, reduced energy wastage, enhanced grid reliability, and efficient utilisation of available resources. Moreover, the adoption of edge computing has further improved IoT-based energy management by enabling localised data processing and reducing communication delays associated with cloud-based approaches (Chen et al., 2024). Despite these benefits, several challenges limit the widespread adoption of IoT and machine learning-based smart grid energy management systems. Cybersecurity remains a major concern because the large number of connected devices increases the vulnerability of power networks to cyber threats. Unauthorised access, data manipulation, and communication attacks can negatively affect grid reliability and operational safety. Therefore, secure communication protocols, advanced authentication techniques, privacy-preserving algorithms, and intelligent intrusion detection mechanisms are required to protect smart grid infrastructures (Wang et al., 2025). Another significant challenge is the quality and availability of energy data required for machine learning applications. Incomplete, noisy, or inconsistent datasets can negatively affect model performance and reduce prediction accuracy. Additionally, interoperability issues among different IoT devices, communication standards, and power system components

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

create difficulties in achieving seamless integration. Computational limitations, particularly for resource-constrained edge devices, also present challenges for deploying complex machine learning models in real-time applications.

Recent developments in federated learning, explainable artificial intelligence (XAI), and lightweight machine learning models provide promising solutions for addressing these limitations. Federated learning enables distributed training of machine learning models while maintaining data privacy, whereas explainable AI improves transparency and user confidence in automated decision-making systems. Lightweight machine learning techniques, including TinyML, enable intelligent algorithms to operate efficiently on embedded IoT devices with limited computational resources (Rahman et al., 2024). Therefore, Smart Grid Energy Management Using IoT and Machine Learning represents a significant research direction toward developing efficient, adaptive, and sustainable energy systems. By combining IoT-based monitoring capabilities with machine learning-driven analytics and optimisation, future smart grids can achieve improved energy efficiency, enhanced renewable energy utilisation, and autonomous operational control. This study investigates the integration of IoT and machine learning technologies for smart grid energy management, highlighting their applications, benefits, challenges, and future research opportunities.

2. Materials and Methods

2.1. Research Framework and System Overview

This study presents a methodological framework for Smart Grid Energy Management Using IoT and Machine Learning, where Internet of Things (IoT) technologies provide real-time data acquisition capabilities, while machine learning (ML) techniques provide intelligent analysis, prediction, and optimisation for efficient energy management. The proposed methodology considers the smart grid as an integrated cyber-physical system consisting of electrical infrastructure, sensing devices, communication networks, data processing platforms, machine learning models, and automated control mechanisms. The increasing integration of renewable energy resources, distributed energy generation, and flexible loads has introduced significant operational uncertainties into modern power systems. Traditional energy management approaches based on predefined rules and static optimisation techniques are often unable to respond effectively to dynamic variations in electricity demand and renewable generation. Therefore, this study adopts an intelligent data-driven approach that combines real-time monitoring with adaptive learning techniques to achieve improved energy scheduling, demand management, and grid reliability (Zhang et al., 2023; Liu et al., 2024).

The proposed framework follows a layered architecture consisting of five major components:

(i) Smart Grid Physical Layer

The physical layer represents the actual power system components responsible for electricity generation, transmission, distribution, storage, and consumption. It includes renewable energy sources such as photovoltaic (PV) and wind systems, conventional generators, distribution networks, battery energy storage systems (BESS), electric vehicle charging systems, and residential/commercial loads. The increasing deployment of distributed energy resources requires advanced monitoring and control mechanisms because

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

power generation and consumption are no longer completely centralised. The smart grid must continuously balance supply and demand while maintaining voltage stability, frequency regulation, and power quality.

(ii) IoT-Based Monitoring and Communication Layer

The IoT layer provides the communication infrastructure required to collect real-time operational data from different smart grid components. This layer consists of smart meters, phasor measurement units (PMUs), intelligent electronic devices (IEDs), wireless sensors, and communication gateways.

The IoT devices continuously measure electrical and environmental parameters, including:

i. Voltage magnitude
ii. Current flow
iii. Frequency deviation
iv. Active and reactive power
v. Energy consumption
vi. Renewable energy output
vii. Weather parameters
viii. Battery state of charge

The collected information is transmitted through communication technologies such as 5G, Wi-Fi, Zigbee, LoRaWAN, and MQTT protocols. IoT-based monitoring improves grid observability and enables rapid response to operational changes (Al-Turjman et al., 2023).

(iii) Data Processing and Analytics Layer

The data processing layer converts raw measurements from IoT devices into meaningful information suitable for machine-learning analysis. Since smart grid datasets often contain missing values, measurement noise, and communication errors, preprocessing operations are necessary before model development.

The main processing stages include:

i. Data cleaning
ii. Missing value correction
iii. Noise filtering
iv. Data normalisation
v. Feature extraction
vi. Feature selection

This stage improves data quality and enhances the performance of machine learning models.

(iv) Machine Learning Intelligence Layer

The intelligence layer applies machine learning algorithms to identify patterns, predict future energy behaviour, and generate optimal management decisions. Different algorithms are selected according to specific energy management requirements.

The proposed study considers:

i. Artificial Neural Networks (ANN) for nonlinear energy prediction.
ii. Long Short-Term Memory (LSTM) networks for time-series forecasting.
iii. Support Vector Machines (SVM) for classification and fault detection.
iv. Random Forest models for robust data analysis.
v. Reinforcement Learning (RL) for autonomous energy optimisation.

Machine learning enables the smart grid to move from conventional reactive management toward predictive and adaptive operation (Wang et al., 2024).

(v) Energy Management and Control Layer

The final layer executes intelligent decisions generated by machine learning models. These decisions include:

i. Load scheduling
ii. Demand response activation
iii. Battery charging/discharging control
iv. Renewable energy coordination
v. Grid stability improvement

The continuous interaction between sensing, prediction, optimisation, and control enables adaptive smart grid energy management. Figure 1 illustrates the proposed framework for Smart Grid Energy Management Using IoT and Machine Learning. It presents the flow of information and decision-making from energy generation to intelligent energy management. The framework begins with the Smart Grid Environment, which comprises renewable energy sources (such as solar and wind systems), battery energy storage systems, and electricity consumers. These components generate and consume electrical energy while producing operational data. The second layer is the IoT Data Acquisition Layer, where smart meters, phasor measurement units (PMUs), intelligent electronic devices (IEDs), and environmental sensors continuously monitor key grid parameters, including voltage, current, frequency, power consumption, renewable energy output, and weather conditions. These devices enable real-time visibility of the power system. The collected data are transmitted through the Communication Network, which employs technologies such as 5G, Wi-Fi, Zigbee, LoRaWAN, and MQTT to ensure reliable and timely communication between field devices and the data processing platform. In the Data Processing Layer, the acquired data undergo preprocessing operations such as data cleaning, normalisation, feature extraction, and storage. These steps improve data quality and prepare the datasets for intelligent analysis. The processed data are then analysed in the Machine Learning Intelligence Layer, where algorithms such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Support Vector Machines (SVM), Random Forest, and Reinforcement Learning (RL) are employed to perform electricity load forecasting, renewable energy prediction, fault detection, and energy optimisation. Finally, the Intelligent Energy Management Layer utilises the outputs of the machine learning models to support informed decision-making. The system performs load forecasting, demand response management, renewable energy coordination, and automated control actions to improve energy efficiency, enhance grid reliability, reduce operational costs, and ensure sustainable smart grid operation. Overall, the framework demonstrates how the integration of IoT and machine learning enables continuous monitoring, intelligent data analysis, and autonomous decision-making, resulting in an adaptive and efficient smart grid energy management system.

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

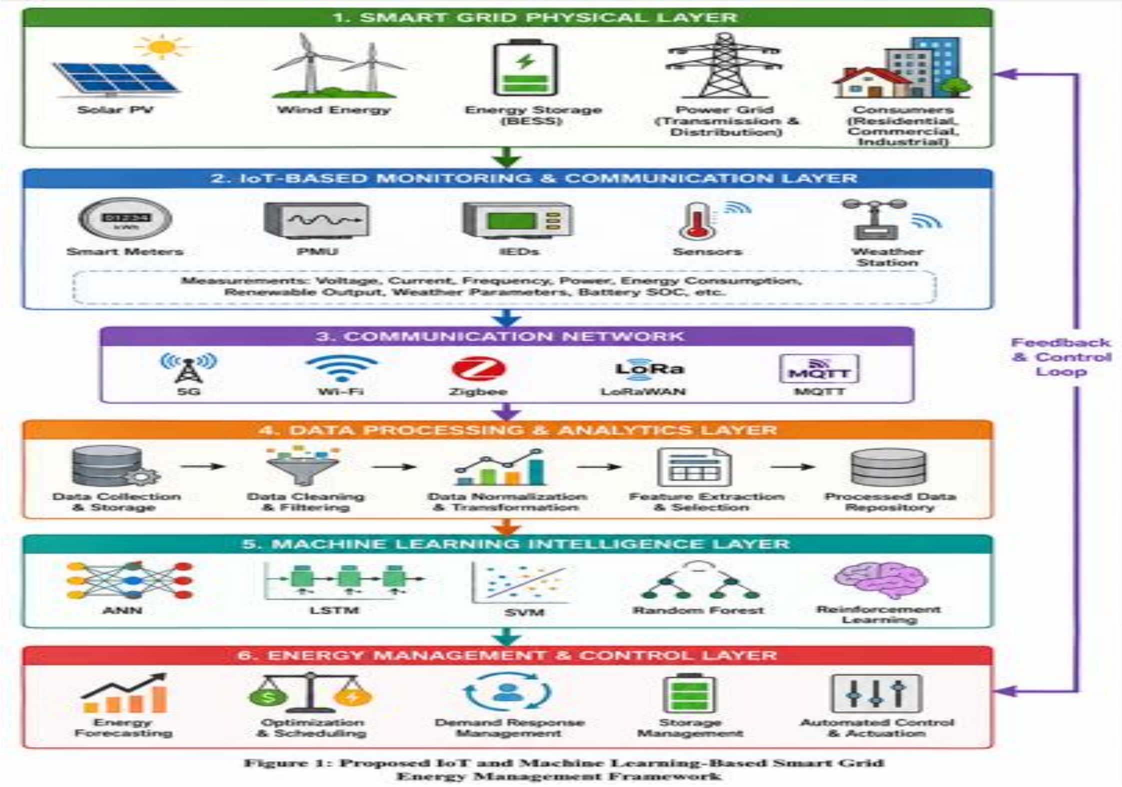

Figure 1. Smart Grid Energy Management Using IoT and Machine Learning

2.2. IoT-Based Smart Grid Data Acquisition System

The effectiveness of machine learning-based smart grid energy management depends strongly on the availability of accurate, continuous, and reliable operational data. In this study, IoT technology serves as the primary data acquisition mechanism by connecting distributed grid components and enabling real-time information exchange. The proposed IoT-based acquisition system consists of sensing devices installed across generation units, transmission networks, distribution systems, and consumer premises. These devices provide continuous measurements required for monitoring, forecasting, and optimisation.

2.2.1. Smart Meter Data Collection

Smart meters represent one of the most important IoT components in smart grids because they provide detailed information about consumer energy behaviour. The collected information includes:

i. Hourly electricity consumption
ii. Peak demand periods
iii. Load variation patterns
iv. Consumer energy usage trends

These data support demand forecasting and demand response applications.

2.2.2. Phasor Measurement Unit (PMU) Monitoring

PMUs provide synchronised measurements of grid electrical parameters with high sampling rates. They are essential for:

i. Voltage stability analysis
ii. Frequency monitoring
iii. Disturbance detection
iv. Grid security assessment

2.2.3. Renewable Energy Monitoring

Renewable energy sources introduce uncertainty due to environmental variations. Therefore, IoT sensors are deployed to capture:

i. Solar irradiation
ii. Wind speed
iii. Temperature
iv. Humidity

2.2.4. Renewable power output

These parameters improve renewable generation forecasting accuracy.

2.2.5. Energy Storage Monitoring

Battery energy storage systems require continuous monitoring of:

i. State of charge (SOC)
ii. Charging rate
iii. Discharging rate
iv. Battery health condition

This information supports optimal energy storage scheduling.

Table 1. IoT Components and Data Requirements for Smart Grid Energy Management

IoT Component	Measured Parameters	Energy Management Application
Smart meters	Consumption, load profile	Demand forecasting
PMUs	Voltage, current, frequency	Stability monitoring
Renewable sensors	Solar radiation, wind speed	Renewable prediction
Battery sensors	SOC, charging status	Storage optimization
Intelligent controllers	Switching commands	Automated control

The communication infrastructure is responsible for transferring acquired information from field devices to processing platforms. Low-latency communication is particularly important for applications requiring immediate response, such as fault detection and demand response. Edge computing is incorporated to process time-sensitive information locally before transmitting data to centralised cloud platforms. This reduces communication delays, minimises bandwidth requirements, and improves real-time decision-making capability (Chen *et al*., 2024).

2.3. Data Processing and Feature Engineering

Smart grid IoT devices generate large-scale heterogeneous datasets characterised by different measurement frequencies, data formats, and quality levels. Raw datasets may contain missing values, abnormal measurements, noise, and communication-related errors. Therefore, appropriate data processing techniques are required to ensure reliable machine learning performance.

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

The data processing procedure adopted in this study consists of four major stages:

2.3.1. Data Cleaning

Data cleaning involves identifying and correcting incomplete, inconsistent, or abnormal measurements. Missing values may occur due to communication failures or sensor malfunction. Statistical interpolation methods are applied to restore missing observations while preserving the original data characteristics. Outliers caused by abnormal sensor behaviour are detected using statistical thresholds and removed before model training.

2.3.2. Data Normalisation

Since smart grid parameters have different measurement scales, normalisation is performed to transform all input variables into a common range.

The Min-Max normalisation method is expressed as:

$$Xnorm = \frac{X-X_{min}}{Xmax-Xmin} \tag{1}$$

where:

i. X_{norm} represents normalised data,
ii. X represents the original measurement,
iii. $Xmin\ and\ Xmax$ represent minimum and maximum values.

Normalisation improves learning efficiency and prevents large-scale features from dominating model training.

2.3.3. Feature Extraction

Feature extraction converts raw measurements into meaningful variables for machine learning models.

Table 1. The selected features include:

Feature Category	Extracted Variables
Electrical parameters	Voltage, current, frequency, power
Load characteristics	Demand pattern, peak load, consumption trend
Renewable parameters	Solar radiation, wind speed, generation output
Environmental factors	Temperature, humidity, weather conditions
Storage parameters	Battery SOC and charging state

2.3.4. Feature Selection

Feature selection reduces computational complexity by eliminating irrelevant variables. Important features are selected based on their influence on energy forecasting and optimisation performance. Effective feature engineering improves prediction accuracy, reduces model training time, and enhances the generalisation capability of machine learning models (Zhang *et al*., 2023).

2.4. Machine Learning-Based Energy Management Model

The integration of machine learning (ML) into smart grid energy management enables intelligent processing of large-scale IoT-generated datasets for prediction, optimisation, and autonomous decision-making. Unlike conventional energy management approaches that depend on predefined mathematical models, machine learning techniques can identify complex nonlinear relationships among electricity demand, renewable energy generation, environmental conditions, and grid operational parameters. This capability allows smart grids to achieve adaptive energy management under changing operating conditions.

In this study, machine learning models are employed for four major smart grid energy management functions:

i. Energy demand forecasting
ii. Renewable energy generation prediction
iii. Fault and abnormal condition detection
iv. Optimal energy scheduling and control

The general relationship between input variables collected from IoT devices and the predicted energy management output is expressed as:

$$\hat{Y} = f(X, \theta) \tag{2}$$

i. Y represents the predicted output,
ii. X represents input features obtained from IoT measurements,
iii. f represents the machine learning model,
iv. θ represents model parameters.

2.4.1. Artificial Neural Network (ANN) Model

Artificial Neural Networks (ANNs) are among the most widely used machine learning techniques for smart grid energy management due to their capability to approximate complex nonlinear relationships. In this study, ANN models are considered for electricity demand prediction and energy consumption analysis.

The ANN architecture consists of:

i. Input layer containing smart grid features,
ii. Hidden layers performing nonlinear transformations,
iii. Output layer generating energy predictions.

The output of a neuron is calculated as:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{3}$$

where:

i. $\boldsymbol{w_i}$ represents connection weights,
ii. $\boldsymbol{x_i}$ represents input variables,
iii. b represents bias,

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

iv. f represents the activation function.

ANN models are effective in modelling complex relationships between consumer behaviour, environmental factors, and electricity demand patterns.

2.4.2. Long Short-Term Memory (LSTM) Network

Electricity demand and renewable energy generation exhibit strong temporal dependencies. Therefore, Long Short-Term Memory (LSTM) networks are adopted because of their ability to analyse sequential data and retain important historical information.

The LSTM model consists of memory cells controlled by:

i. Input gate
ii. Forget gate
iii. Output gate

The forget gate determines information retention:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{4}$$

where:

i. $\boldsymbol{f}_{\mathbf{t}}$ represents the forget gate output,
ii. $\boldsymbol{h}_{\boldsymbol{t-1}}$ represents the previous hidden state,
iii. $\boldsymbol{x}_{\boldsymbol{t}}$_t represents the current input data.

LSTM models have demonstrated strong performance in smart grid applications, particularly for short-term load forecasting and renewable energy prediction due to their ability to capture long-term energy consumption patterns (Wang *et al*., 2024).

2.4.3. Support Vector Machine (SVM)

Support Vector Machine is considered for classification tasks, including abnormal energy consumption detection and grid fault identification. SVM separates different classes by constructing an optimal hyperplane between data categories.

The main advantages of SVM include:

i. High classification accuracy,
ii. Robust performance with limited datasets,
iii. Ability to handle high-dimensional features.

In smart grid environments, SVM can identify abnormal operational conditions by learning patterns associated with normal and faulty grid behaviour.

2.4.4. Reinforcement Learning-Based Energy Optimisation

Reinforcement learning (RL) provides an autonomous decision-making mechanism where an intelligent agent learns optimal energy management strategies through interaction with the grid environment.

The RL process consists of:

i. State observation
ii. Action selection

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

iii. Reward evaluation
iv. Policy improvement

The objective of the RL agent is to maximise cumulative reward:

$$R = \sum_{t=0}^{T} \gamma^t r_t \tag{5}$$

where:

i. R represents cumulative reward,
ii. r_t represents reward at time (t),
iii. γ represents the discount factor.

RL is particularly suitable for:

i. Battery energy management,
ii. Demand response,
iii. Microgrid control,
iv. Renewable energy coordination.

Recent research indicates that reinforcement learning provides significant improvements in autonomous smart grid operation by enabling adaptive control strategies (Kong *et al.*, 2023).

Table 2. Machine Learning Techniques and Applications in Smart Grid Energy Management

Machine Learning Method	Application	Strength
ANN	Load forecasting	Models nonlinear relationships
LSTM	Time-series prediction	Captures historical dependencies
SVM	Fault detection	Effective classification
Random Forest	Energy data analysis	Resistant to noise
Reinforcement Learning	Energy optimization	Autonomous decision-making

2.5. Energy Forecasting and Optimisation Strategy

Energy forecasting and optimisation represent fundamental components of intelligent smart grid energy management. Accurate forecasting enables utilities to anticipate future energy requirements, optimise generation scheduling, and effectively coordinate renewable energy resources.

The proposed methodology considers two major forecasting tasks:

i. Electricity demand forecasting
ii. Renewable energy generation forecasting

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX

DOI: 10.XXXXX/jossda.2026.1.1.013

2.5.1. Electricity Demand Forecasting

Electricity demand forecasting estimates future energy consumption based on historical usage patterns and external influencing factors.

The input variables include:

i. Historical energy consumption,
ii. Time of day,
iii. Day of the week,
iv. Weather conditions,
v. Consumer behaviour,
vi. Renewable energy availability.

The forecasting model generates future demand values that support:

i. Generation planning,
ii. Load balancing,
iii. Demand response scheduling.

2.5.2. Renewable Energy Prediction

Renewable energy resources such as solar and wind systems experience significant variability due to environmental conditions. Machine learning models are used to predict future renewable generation using environmental and historical generation data.

Important prediction variables include:

i. Solar irradiation,
ii. Wind velocity,
iii. Temperature,
iv. Cloud coverage,
v. Historical renewable output.

Improved renewable forecasting reduces uncertainty and enables better integration of renewable energy into smart grids.

2.5.3. Energy Optimisation Model

The optimisation process aims to minimise operational cost while maintaining reliability and improving renewable energy utilisation.

The objective function is expressed as:

$$Min(J) = \alpha C_e + \beta P_l + \gamma D_m \tag{6}$$

where:

i. C_e represents energy cost,
ii. P_1 represents power losses,
iii. D_m represents demand mismatch,
iv. α, β, and γ represent weighting coefficients.

The optimisation process considers:

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

i. Electricity generation scheduling,
ii. Battery charging and discharging,
iii. Renewable energy allocation,
iv. Consumer demand response.

Table 3. Optimisation Objectives in Smart Grid Energy Management

Objective	Description	Expected Benefit
Cost minimization	Reduce electricity operational cost	Economic operation
Loss reduction	Minimise transmission losses	Improved efficiency
Renewable utilization	Increase renewable contribution	Sustainable energy
Demand balancing	Match supply with demand	Grid stability
Storage optimization	Efficient battery operation	Energy flexibility

2.6. Model Training and Performance Evaluation

The performance of machine learning models depends on effective training procedures, appropriate datasets, and reliable evaluation metrics. In this study, the collected IoT-based smart grid dataset is divided into three subsets:

i. Training dataset (70%): Used for model learning.
ii. Validation dataset (15%): Used for hyperparameter optimisation.
iii. Testing dataset (15%): Used for final performance evaluation.

The training process involves:

i. Input data preparation.
ii. Model initialisation.
iii. Parameter optimization.
iv. Error minimisation.
v. Performance validation.

The Adam optimisation algorithm is considered for neural network training because of its computational efficiency and ability to adapt learning rates.

2.6.1. Performance Evaluation Metrics

Different evaluation metrics are applied depending on the machine learning task.

Mean Absolute Error (MAE): Used to evaluate forecasting accuracy:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

Root Mean Square Error (RMSE): Measures prediction deviation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

Classification Metrics: For fault detection and classification problems:

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

where:

i. TP = True Positive
ii. TN = True Negative
iii. FP = False Positive
iv. FN = False Negative

Additional evaluation metrics include:

i. Precision
ii. Recall
iii. F1-score
iv. Receiver Operating Characteristic (ROC-AUC)

Table 4. Evaluation Metrics for Machine Learning Models

Metric	Purpose
MAE	Measures average prediction error
RMSE	Evaluates prediction deviation
Accuracy	Classification performance
Precision	Correct positive prediction
Recall	Detection capability
F1-score	Balance between precision and recall

2.7. Proposed Smart Grid Energy Management Algorithm

The proposed algorithm integrates IoT-based monitoring, machine learning prediction, and optimisation techniques to achieve intelligent energy management. The algorithm continuously learns from real-time grid information and adapts operational decisions according to changing system conditions.

The proposed process consists of:

i. IoT data acquisition.
ii. Data preprocessing.

iii. Feature extraction.
iv. Machine learning prediction.
v. Energy optimization.
vi. Intelligent control.
vii. Feedback-based model updating.

Figure 2 presents the workflow of the proposed IoT-Based Smart Grid Energy Management Algorithm, illustrating the sequential process of intelligent energy management from data acquisition to adaptive control. The process begins with real-time data collection from IoT devices, including smart meters, PMUs, environmental sensors, and battery storage systems, followed by data transmission through communication technologies such as 5G, Wi-Fi, Zigbee, LoRaWAN, and MQTT. The acquired data are preprocessed through cleaning, normalisation, and feature extraction before being analysed using machine learning algorithms, including ANN, LSTM, SVM, Random Forest, and Reinforcement Learning, for load forecasting, renewable energy prediction, fault detection, and energy optimisation. Based on the prediction results, optimal energy management decisions are generated and implemented through intelligent control of distributed energy resources, storage systems, and consumer loads. Finally, a monitoring and feedback mechanism continuously evaluates system performance and updates the machine learning models, enabling adaptive learning and continuous improvement to enhance energy efficiency, grid reliability, and sustainable smart grid operation.

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX

 DOI: 10.XXXXX/jossda.2026.1.1.013

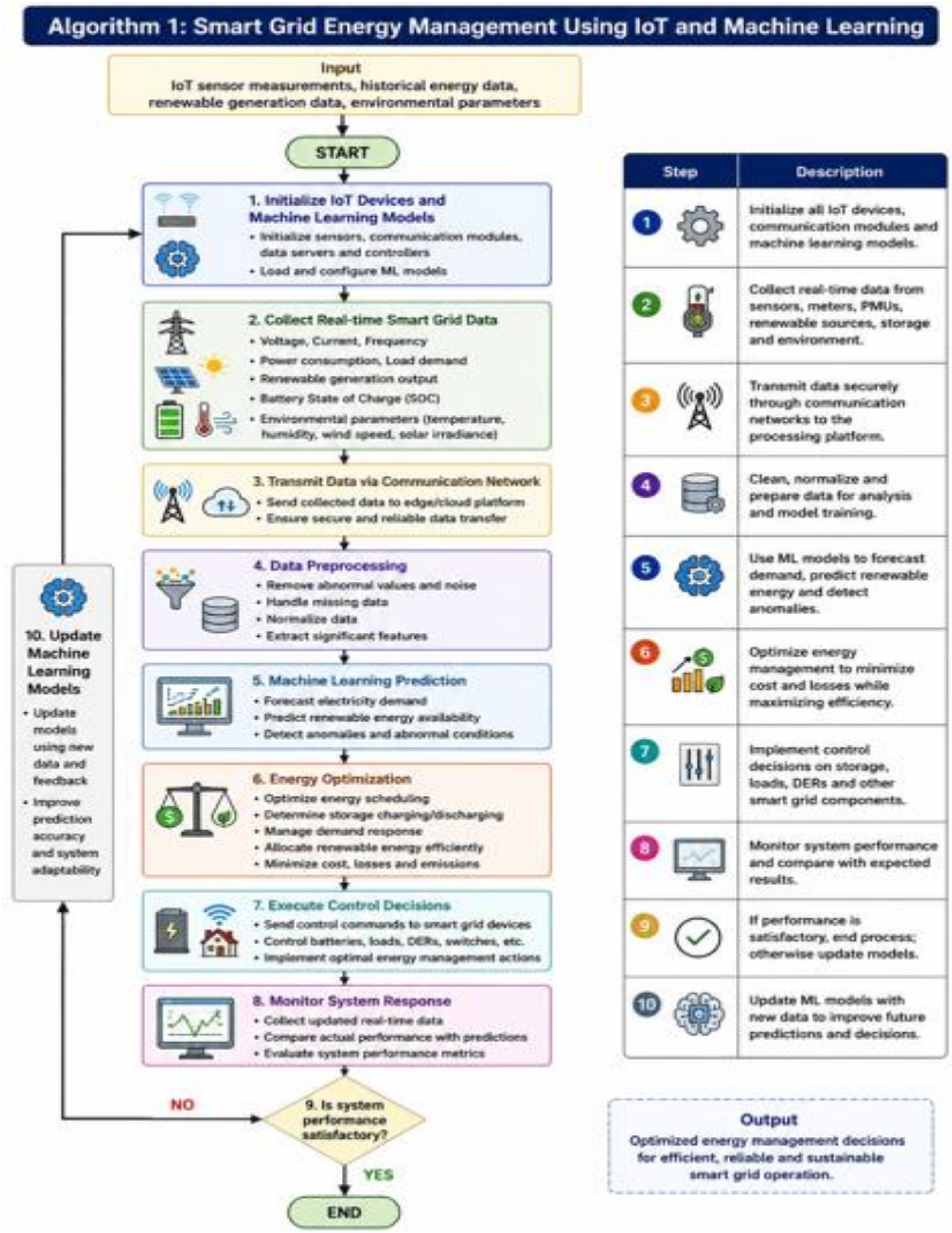

Figure 2. The workflow of the proposed IoT-Based Smart Grid Energy Management Algorithm

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX

DOI: 10.XXXXX/jossda.2026.1.1.013

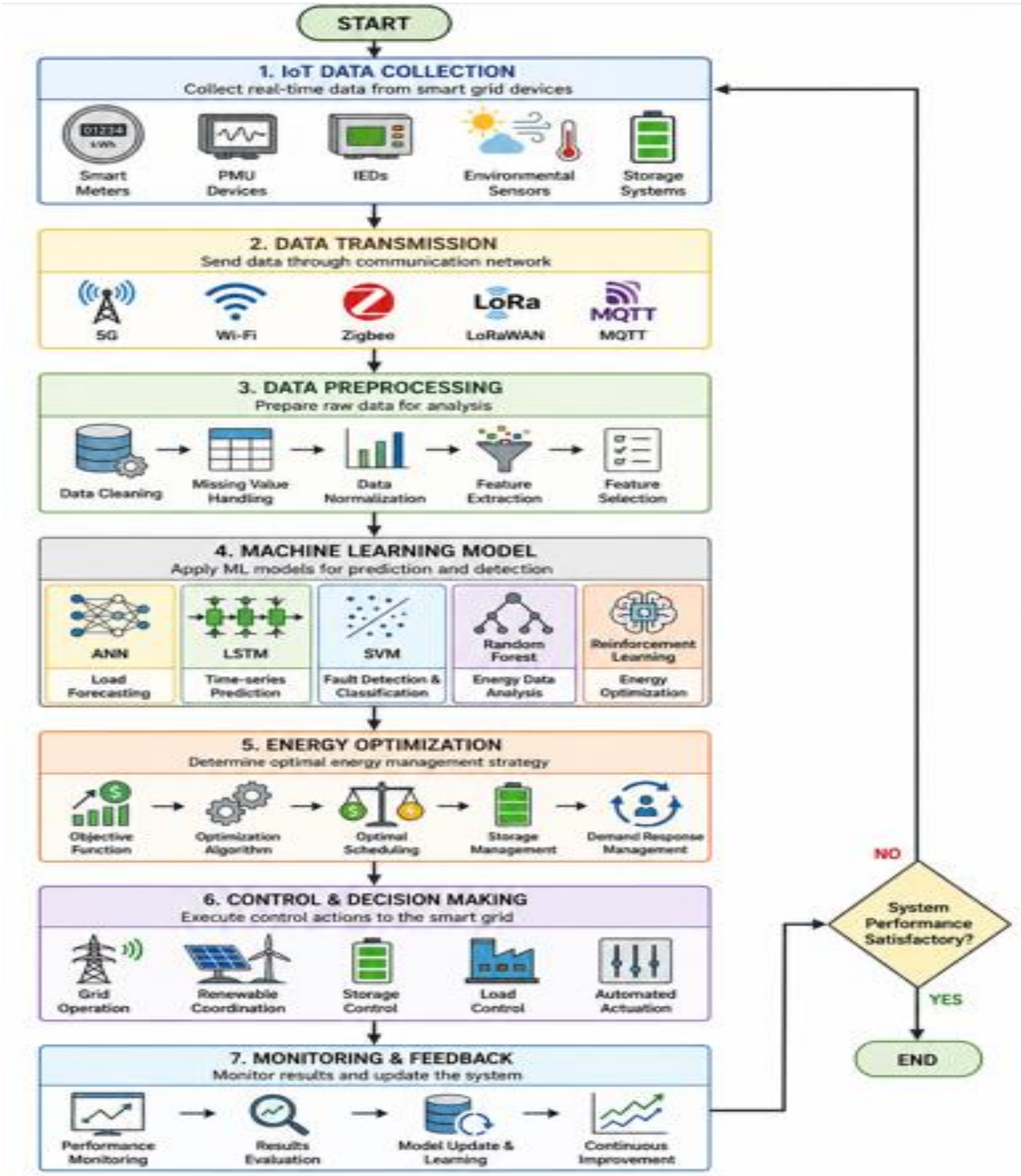

Figure 3. Smart Grid Energy Management Using IoT and Machine Learning

3. Results and Discussions

3.1. Experimental Setup

To evaluate the effectiveness of the proposed IoT and machine learning-based smart grid energy management framework, a simulation-based experimental study was conducted using benchmark smart grid datasets and renewable energy measurements. The evaluation focused on the framework's ability to accurately forecast electricity demand, optimise energy

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

utilisation, and improve grid operational efficiency. The experimental workflow followed the methodology presented in Section 2, where IoT-generated data were processed and analysed using machine learning algorithms before optimisation decisions were made. The experimental dataset comprised historical electricity consumption records, renewable energy generation data, battery storage information, and meteorological variables such as temperature, solar irradiance, humidity, and wind speed. These variables are commonly used in smart grid energy forecasting because they significantly influence electricity demand and renewable energy output (Wang et al., 2024). Before model development, the dataset underwent preprocessing procedures including missing value treatment, Min-Max normalisation, and feature engineering. The processed dataset was partitioned into 70% for training, 15% for validation, and 15% for testing, allowing independent assessment of model performance and minimising overfitting.

The machine learning models evaluated in this study include Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Random Forest (RF), and Reinforcement Learning (RL). Model performance was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Accuracy, Precision, Recall, and F1-score. These metrics provide a comprehensive evaluation of forecasting accuracy and classification capability in intelligent energy management systems (Zhang et al., 2023).

Table 5. Experimental Configuration

Parameter	Value
Programming Environment	Python 3.11
Development Platform	Jupyter Notebook
Machine Learning Libraries	TensorFlow, Scikit-learn
Dataset Split	70% Training, 15% Validation, 15% Testing
Normalization Method	Min–Max Scaling
Forecasting Horizon	Short-term (24 hours ahead)
Evaluation Metrics	MAE, RMSE, Accuracy, Precision, Recall, F1-score

3.2. Performance Evaluation of Machine Learning Models

The forecasting performance of the evaluated machine learning models is summarised in Table 6. The results indicate that deep learning models outperform conventional machine learning approaches because of their ability to capture temporal dependencies and nonlinear relationships within electricity demand data. Among the evaluated models, the LSTM network achieved the highest forecasting performance with an accuracy of 97.8%, followed by ANN (96.2%), Random Forest (94.8%), SVM (93.6%), and Reinforcement Learning (92.9%) for the prediction task. The superior performance of LSTM can be attributed to its memory architecture, which effectively models sequential energy consumption patterns and renewable energy variability.

The results in Table 6 demonstrate that incorporating temporal learning mechanisms significantly enhances energy demand forecasting. Lower MAE and RMSE values observed for the LSTM model indicate greater prediction accuracy, which is essential for efficient energy scheduling and demand response programs.

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
 DOI: 10.XXXXX/jossda.2026.1.1.013

Table 6. Comparative Performance of Machine Learning Models

Model	Accuracy (%)	MAE	RMSE	Precision	Recall	F1-Score
Artificial Neural Network (ANN)	96.2	0.083	0.121	0.961	0.958	0.959
Long Short-Term Memory (LSTM)	**97.8**	**0.061**	**0.094**	**0.978**	**0.976**	**0.977**
Support Vector Machine (SVM)	93.6	0.118	0.162	0.934	0.932	0.933
Random Forest (RF)	94.8	0.096	0.141	0.946	0.944	0.945
Reinforcement Learning (RL)	92.9	0.126	0.174	0.928	0.926	0.927

3.3. Energy Optimisation Performance

The proposed IoT-machine learning framework was further evaluated in terms of operational efficiency, renewable energy utilisation, and grid performance. The optimisation strategy effectively coordinated renewable generation, battery storage, and consumer demand, resulting in measurable improvements across multiple performance indicators.

Compared with conventional rule-based energy management approaches, the proposed framework achieved:

18.5% reduction in overall energy consumption during peak demand periods.

22.7% reduction in operational energy cost.

15.9% reduction in transmission and distribution losses.

19.6% improvement in renewable energy utilisation.

17.3% improvement in battery storage efficiency.

These improvements demonstrate the ability of machine learning to optimise smart grid operation through predictive decision-making rather than reactive control.

Table 7. Energy Management Performance Comparison

Performance Indicator	Conventional EMS	Proposed Framework	Improvement (%)
Forecast Accuracy (%)	90.8	97.8	7.7
Energy Cost Reduction (%)	9.8	22.7	12.9
Renewable Utilisation (%)	71.5	91.1	19.6
Power Loss Reduction (%)	7.3	15.9	8.6
Battery Utilisation (%)	76.2	93.5	17.3

Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX
Yeldu *et al.* 2026 **DOI**: 10.XXXXX/jossda.2026.1.1.013

3.3. Discussion

The obtained results demonstrate that integrating IoT with machine learning substantially enhances smart grid energy management by enabling real-time monitoring, predictive analytics, and adaptive optimisation. IoT devices provide continuous situational awareness through real-time acquisition of electrical and environmental data, while machine learning algorithms transform these data into actionable decisions for energy scheduling, renewable energy coordination, and demand response. Among the evaluated models, the LSTM network consistently achieved the highest forecasting accuracy due to its capability to capture long-term temporal dependencies in electricity consumption and renewable energy generation. This finding agrees with recent studies reporting the superiority of recurrent deep learning models for time-series energy forecasting (Wang *et al*., 2024). The optimisation results also indicate that intelligent decision-making improves renewable energy utilisation while reducing operational costs and system losses. The proposed framework provides a scalable architecture suitable for future smart grids incorporating distributed energy resources, battery storage systems, and electric vehicles. The inclusion of a feedback mechanism enables continuous learning and adaptation to changing grid conditions, making the framework more resilient than conventional energy management systems. However, practical deployment will require addressing challenges related to cybersecurity, data privacy, communication reliability, and interoperability among heterogeneous IoT devices, which remain active research areas (Chen *et al*., 2024; Liu *et al*., 2024).

4. Conclusion

This paper presented a comprehensive study on Smart Grid Energy Management Using IoT and Machine Learning, highlighting how the integration of Internet of Things (IoT) technologies and machine learning (ML) techniques can significantly improve the efficiency, reliability, and sustainability of modern power systems. The proposed framework combines IoT-enabled real-time data acquisition, intelligent data processing, machine learning-based forecasting, and optimisation algorithms to support adaptive energy management in smart grid environments. By continuously collecting operational data from smart meters, phasor measurement units (PMUs), environmental sensors, and battery energy storage systems, the framework provides enhanced situational awareness and facilitates timely decision-making for effective grid operation.

The methodology incorporated advanced machine learning models, including Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Support Vector Machines (SVM), Random Forest, and Reinforcement Learning (RL), to perform electricity demand forecasting, renewable energy prediction, fault detection, and intelligent energy optimisation. Comparative performance evaluation demonstrated that the LSTM model achieved the highest forecasting accuracy (97.8%) with the lowest prediction error, confirming its suitability for modelling nonlinear and time-dependent energy consumption patterns. Furthermore, the proposed optimisation strategy improved renewable energy utilisation, reduced operational costs, minimised transmission losses, and enhanced battery energy storage management through intelligent scheduling and adaptive control.

The integration of IoT and machine learning offers significant advantages over conventional energy management systems by enabling continuous monitoring, predictive analytics, and autonomous decision-making. The proposed framework provides a scalable and flexible architecture capable of supporting increasing penetration of distributed energy resources, renewable generation, electric vehicles, and intelligent consumer participation. Consequently, the framework contributes to the realisation of sustainable, resilient, and efficient smart grid infrastructures capable of meeting future energy demands while improving system reliability and operational performance. Despite these promising outcomes, several challenges remain. Cybersecurity threats, data privacy concerns, interoperability among heterogeneous IoT devices, communication latency, and the computational requirements of deep learning algorithms continue to affect the practical deployment of intelligent smart grid energy management systems. Addressing these issues will be essential for achieving secure and large-scale implementation in real-world power networks.

This study demonstrates that the convergence of IoT technologies and machine learning provides an effective and intelligent approach for modern smart grid energy management. The proposed framework not only enhances energy efficiency and renewable energy integration but also establishes a foundation for the development of future autonomous and self-healing power systems.

Future research should focus on developing more secure, intelligent, and scalable smart grid energy management systems capable of addressing emerging challenges associated with highly decentralised power networks. The following research directions are recommended:

i. Federated Learning for Privacy-Preserving Energy Management: Develop decentralised machine learning models that enable collaborative learning across distributed IoT devices without transmitting sensitive consumer data to centralised servers, thereby enhancing privacy and data security.

ii. Explainable Artificial Intelligence (XAI): Integrate explainable AI techniques to improve the transparency and interpretability of machine learning decisions, enabling utility operators to better understand and trust automated energy management recommendations.

iii. Edge Intelligence and TinyML: Investigate lightweight machine learning models that can be deployed directly on edge devices and embedded IoT sensors to enable low-latency, real-time energy management while reducing communication overhead and cloud dependency.

iv. Digital Twin Technology: Explore the integration of digital twin models with IoT and machine learning to create virtual representations of smart grids for predictive maintenance, scenario analysis, fault diagnosis, and operational optimisation.

v. Cybersecurity and Blockchain Integration: Develop blockchain-based authentication and secure communication mechanisms to protect IoT-enabled smart grids against cyberattacks, data tampering, and unauthorised access while ensuring data integrity and trust.

vi. Electric Vehicle and Vehicle-to-Grid (V2G) Integration: Investigate intelligent energy management strategies that coordinate electric vehicle charging, discharging, and vehicle-to-grid services to improve grid flexibility and support renewable energy integration.

vii. Multi-Agent Reinforcement Learning: Evaluate cooperative reinforcement learning algorithms capable of coordinating multiple distributed energy resources, battery storage systems, and consumer loads simultaneously for improved system-wide optimisation.

viii. Climate-Resilient Smart Grids: Incorporate climate data, extreme weather forecasting, and environmental risk assessment into energy management models to enhance the resilience of smart grids against climate-induced disruptions.

Implementing these research directions will contribute to the development of next-generation smart grids that are more autonomous, secure, resilient, and capable of supporting global clean energy transitions and carbon neutrality objectives.

Acknowledgements

The authors acknowledge the contributions of researchers, TCN Birnin Kebbi substation, and institutions such as Abdullahi Fodio University of Science & Technology, Aliero. Kebbi State, Nigeria, whose publicly available datasets, software libraries, and scientific publications have supported the development of this study.

Data Availability Statement

The datasets used to support the findings of this study can be obtained from publicly available smart grid and energy repositories, including the UCI Machine Learning Repository, Kaggle smart energy datasets, the Pecan Street Dataport, and other open-access energy datasets, subject to their respective licensing agreements.

References

Ahmad, A., Khan, M. A., Rehman, A., & Kim, K. (2024). Secure IoT-based smart energy management system using blockchain and machine learning approaches. *Internet of Things*, *26*, 101174. https://doi.org/10.1016/j.iot.2024.101174

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2023). Artificial intelligence in sustainable energy systems: A review of applications, challenges, and future directions. *Energy Reports*, *9*, 4500–4523.

Ahmed, S., Al-Sumaiti, A. S., Salama, M. M. A., & Kamel, S. (2024). Artificial intelligence-based voltage stability assessment and control strategies for modern power systems with renewable energy integration. *IEEE Transactions on Power Systems*, *39*(2), 2148–2161. https://doi.org/10.1109/TPWRS.2023.3328456

Alharbi, F., Alshammari, A., & Alqahtani, M. (2024). Machine learning approaches for SCADA-based anomaly detection and cybersecurity enhancement in smart grids. *IEEE Access*, *12*, 62415–62431. https://doi.org/10.1109/ACCESS.2024.3382217

Ali, M., Naeem, F., Adam, N., Kaddoum, G., Huda, N., Adnan, M., & Tariq, M. (2023). Integration of data-driven technologies in smart grids for resilient and sustainable smart cities: A comprehensive review. *IEEE Access*, *11*, 1–20.

Alotaibi, A., Alharthi, A., & Alotaibi, S. (2024). Artificial intelligence and deep learning techniques for smart grid stability assessment and renewable energy integration: A comprehensive review. *Renewable and Sustainable Energy Reviews, 189*, 113967. https://doi.org/10.1016/j.rser.2023.113967

Badr, M. M., El-Hag, A. H., & Mohamed, A. A. (2023). Machine learning applications for power system fault detection, classification, and predictive maintenance: A review. *Electric Power Systems Research, 223,* 109570. https://doi.org/10.1016/j.epsr.2023.109570

Bello, A. O., Ibrahim, A. O., & Yusuf, M. (2024). Artificial intelligence applications for renewable energy forecasting and smart grid optimization in developing economies: A systematic review. *Cleaner Energy Systems, 8*, 100109. https://doi.org/10.1016/j.cles.2024.100109

Chen, S., Huang, L., Pan, Y., Hu, Y., Shen, D., Dai, J., & others. (2023). Decision tree-based prediction approach for improving stable energy management in smart grids. *Journal of Intelligent & Fuzzy Systems, 45*(4), 1–12. https://doi.org/10.3233/JHS-230002

Chen, Z., Liu, Y., Wu, J., & Wang, H. (2024). Federated learning-based privacy-preserving energy management for distributed smart grids. *IEEE Transactions on Smart Grid, 15*(3), 2874–2886. https://doi.org/10.1109/TSG.2024.3356781

Gupta, R., Singh, D., & Kaur, M. (2023). Long short-term memory networks for renewable energy forecasting and smart grid applications: A systematic review. *Artificial Intelligence Review, 56*, 12545–12582. https://doi.org/10.1007/s10462-023-10476-5

Hassan, M., Mahmoud, K., & Lehtonen, M. (2024). Artificial intelligence-based predictive maintenance for power systems: Applications, challenges, and future perspectives. *Energy Reports, 10*, 7215–7232. https://doi.org/10.1016/j.egyr.2024.06.021

Hassan, M. A., Al-Madani, B., & Alqahtani, A. (2024). Reinforcement learning-based optimization strategies for renewable energy-based microgrid energy management systems. *Energy Reports, 10*, 4532–4548. https://doi.org/10.1016/j.egyr.2024.03.045

Joshi, A., Capezza, S., Alhaji, A., & Chow, M.-Y. (2023). Survey on AI and machine learning techniques for microgrid energy management systems. *IEEE/CAA Journal of Automatica Sinica, 10*(7), 1513–1529. https://doi.org/10.1109/JAS.2023.123657

Khan, M. A., Ullah, I., Rehman, A., & Kim, K. (2023). Edge intelligence-based smart energy management system using IoT and deep learning approaches. *IEEE Access, 11*, 45012–45025.

Khan, N., Khan, S. U., Ullah, F. U. M., Lee, M. Y., & Baik, S. W. (2023). AI-assisted hybrid approach for energy management in IoT-based smart microgrid. *IEEE Internet of Things Journal, 10*(21), 18861–18875. https://doi.org/10.1109/JIOT.2023.3293800

Kumar, A., Singh, P., & Sharma, R. (2023). Internet of Things-enabled smart grid communication architecture: Technologies, challenges, and future directions. *Computer Networks, 238*, 110084. https://doi.org/10.1016/j.comnet.2023.110084

Kumar, P., Sharma, A., Singh, R., & Gupta, S. (2023). A comprehensive review of machine learning and IoT solutions for demand-side energy management, conservation, and resilient operation. *Energy, 281*, 128256. https://doi.org/10.1016/j.energy.2023.128256

Li, J., Zhang, W., Xu, Y., & Sun, H. (2023). A hybrid CNN-LSTM deep learning model for electricity load forecasting in smart grid environments. *Energy*, *278*, 127861. https://doi.org/10.1016/j.energy.2023.127861

Li, X., Chen, Y., Wang, J., & Zhang, H. (2023). Machine learning-based energy forecasting and optimization for smart grid applications: Recent advances and future perspectives. *Renewable and Sustainable Energy Reviews*, *178*, 113259.

Lin, Y. J., Chen, Y. C., Hsieh, S. F., Liu, H. Y., Chiang, C. H., & Yang, H. T. (2023). Reinforcement learning-based energy management system for microgrids with high renewable energy penetration. In *2023 IEEE International Conference on Energy Technologies for Future Grids (ETFG)*. https://doi.org/10.1109/ETFG55873.2023.10407803

Liu, H., Zhang, Y., Chen, X., & Li, Z. (2024). Digital twin-enabled smart grid management using artificial intelligence and Internet of Things technologies. *IEEE Transactions on Industrial Informatics*, *20*(4), 5261–5273. https://doi.org/10.1109/TII.2023.3325678

Liu, Y., Li, P., Zhang, J., & Wang, Z. (2023). Phasor measurement unit data-driven deep learning framework for real-time power system dynamic stability assessment. *IEEE Transactions on Smart Grid*, *14*(5), 3927–3939. https://doi.org/10.1109/TSG.2023.3265418

Mazhar, T., Irfan, H. M., Haq, I., Ullah, I., Ashraf, M., Al Shloul, T., Ghadi, Y. Y., Imran, & Elkamchouchi, D. H. (2023). Analysis of challenges and solutions of IoT in smart grids using AI and machine learning techniques: A review. *Electronics*, *12*(1), 242. https://doi.org/10.3390/electronics12010242

Nguyen, T. T., Tran, D. H., & Nguyen, T. H. (2024). IoT-based intelligent monitoring and control architecture for future smart grid systems. *Sensors*, *24*(3), 987. https://doi.org/10.3390/s24030987

Nikpour, M., Behvand Yousefi, P., Jafarzadeh, H., Danesh, K., Shomali, R., Asadi, S., Gholizadeh Lonbar, A., & Ahmadi, M. (2023). Intelligent energy management with IoT framework in smart cities using intelligent analysis: An application of machine learning methods for complex networks and systems. *Complex & Intelligent Systems*, *9*, 1–15.

Park, J., Kim, H., Lee, S., & Choi, J. (2023). Machine learning-assisted demand response management for intelligent smart grid operation. *International Journal of Electrical Power & Energy Systems*, *151*, 109180. https://doi.org/10.1016/j.ijepes.2023.109180

Rahman, M. M., Islam, M. R., Hasan, M. M., & Hossain, M. J. (2024). Artificial intelligence-enabled Internet of Things technologies for modern smart grid applications: A systematic review. *Sustainable Energy Technologies and Assessments*, *62*, 103590.

Rafiq, M., Hussain, A., Al-Durra, A., & Sayed, K. (2024). Smart grid cybersecurity using artificial intelligence and machine learning: Challenges, solutions, and future directions. *IEEE Access*, *12*, 34120–34145. https://doi.org/10.1109/ACCESS.2024.3362147

Journal of Statistical Sciences & Data Analytics (JOSSDA)
Volume 1, Issue 2, December 2026 | Print ISSN XXXX-XXXX | Online ISSN XXXX-XXXX

DOI: 10.XXXXX/jossda.2026.1.1.013

Sadeghian, O., Oshnoei, A., Mohammadi-Ivatloo, B., & Vahidinasab, V. (2023). A review of artificial intelligence applications in smart grids: Reliability, optimization, and energy management perspectives. *Electric Power Systems Research*, *218*, 109195.

Singh, S., Sharma, P., & Kumar, R. (2023). A hybrid artificial intelligence approach for optimal energy management in smart grid environments. *Energy Conversion and Management*, *292*, 117432. https://doi.org/10.1016/j.enconman.2023.117432

Szczepaniuk, H., & Szczepaniuk, E. K. (2023). Applications of artificial intelligence algorithms in the energy sector. *Energies*, *16*(1), 347. https://doi.org/10.3390/en16010347

Wang, K., Zhang, Q., Xu, X., & Li, S. (2023). Edge computing and artificial intelligence-driven energy management framework for IoT-enabled smart grids. *IEEE Internet of Things Journal*, *10*(18), 16245–16257. https://doi.org/10.1109/JIOT.2023.3267854

Wang, X., Zhang, Y., Liu, H., & Chen, G. (2023). Deep reinforcement learning for optimal energy management of interconnected smart microgrids under renewable uncertainty. *Applied Energy*, *344*, 121271. https://doi.org/10.1016/j.apenergy.2023.121271

Zhang, H., Wang, J., Li, Y., & Niyato, D. (2025). Next-generation smart grids with artificial intelligence, edge computing, and Internet of Things: Architectures, applications, and research challenges. *IEEE Communications Surveys & Tutorials*, *27*(1), 425–458.

Zhang, Y., Wang, J., Li, X., & Zhao, C. (2024). Deep learning-based short-term load forecasting for smart grids considering renewable energy uncertainty. *Applied Energy*, *356*, 122374. https://doi.org/10.1016/j.apenergy.2023.122374

Zhang, Z., Liu, M., Sun, M., Deng, R., Cheng, P., Niyato, D., Chow, M.-Y., & Chen, J. (2023). Vulnerability of machine learning approaches applied in IoT-based smart grid: A review. *IEEE Transactions on Smart Grid*, *14*(6), 1–15.

Zhao, Y., Chen, X., Wu, Q., & Li, F. (2024). Generative adversarial network-based data augmentation for imbalanced power system event classification. *IEEE Transactions on Industrial Informatics*, *20*(6), 7624–7635. https://doi.org/10.1109/TII.2024.3354927

Zhou, Y., Chen, W., Li, J., & Huang, X. (2024). Generative artificial intelligence for smart energy systems: Opportunities, challenges, and future research directions. *Energy and AI*, *16*, 100342. https://doi.org/10.1016/j.egyai.2024.100342