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Machine Learning-Based Renewable Energy Forecasting and Priority Load Management for Smart Energy Systems

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Reliable electricity is not just a convenience; it is a basic human necessity. However, a huge number of people in developing countries face daily power cuts that disrupt their everyday lives. When load demand exceeds the available energy supply, high-priority services such as emergency hospitals (particularly ICUs, ventilators, and surgical units), emergency services, street lighting, railways, airport operations, and critical household appliances such as refrigerators, water pumps, and heating or cooling systems may fail to function properly. This challenge is further worsened by the heavy reliance on costly and environmentally damaging fossil fuels. Although solar and wind energy are cleaner and more affordable, managing them is still a challenge because they do not produce a steady supply of power—their output rises and falls with the weather. This paper introduces a smart energy management system that uses a Long Short-Term Memory (LSTM) model to predict renewable energy output and an XGBoost model to predict electricity consumption by the load. The forecasting models were developed and tested using four real-world datasets that capture solar generation, wind generation, and the electricity needs of both high-priority and low-priority loads. Using these predicted values, a rule-based control system was designed and simulated in MATLAB/Simulink to efficiently manage the distribution of power. The system classifies electrical loads into two groups: high-priority and low-priority loads, and guarantees that high-priority loads are always supplied with power before others. The backup generator kicks in automatically only when renewable power generation is insufficient to supply high-priority loads, which helps keep operational costs low and reduces reliance on non-renewable energy sources. The proposed forecasting models have shown strong and consistent performance on the four datasets. For solar generation forecasting, the LSTM model achieved an R^2 of 0.9577, MSE of 29.72, RMSE of 5.45, and MAE of 2.75, improving over baseline values of R^2=0.94, MSE=45.00, RMSE=20.1, and MAE=15.2. For wind generation forecasting, the LSTM model achieved an R^2 of 0.9537, MSE of 143.20, RMSE of 11.97, and MAE of 7.83, compared to baseline values of R^2=0.94, MSE=180.00, RMSE=20.1, and MAE=15.2. The XGBoost model's results for high priority load demand forecasting were R^2 =0.9007, MSE=10.32, RMSE=3.21 and MAE=2.61, compared to the baseline R^2=0.85, MSE=56.72, RMSE=7.48 and MAE=5.90. For low priority load demand forecasting, the XGBoost model achieved an R^2 of 0.9004, MSE of 126.78, RMSE of 11.26, and MAE of 9.13, compared to baseline values of R^2=0.86, MSE=130.00, RMSE=13.00, and MAE=13.00. The simulation outcomes further validate that the proposed system reliably delivers an uninterrupted power supply to high-priority loads under varying operating conditions, whether renewable generation is high, limited, or completely insufficient, while considerably reducing the unnecessary activation of backup generators.

Keywords: LSTM, XGBoost, High-Priority Load, Low-Priority Load, MATLAB/Simulink

Introduction:

Electric power is one of the essential factors in human development. Electricity is needed for the proper operation of every building, school, hospital, home, factory, and office. In many developing countries, maintaining a stable electricity supply is difficult because of the mismatch between load demand and the supply of electricity. Load shedding is an issue that arises when electricity demand exceeds supply. In load shedding, the electricity supply is cut off in some areas to meet the energy requirements of others. The loss of electricity for several hours is a major concern, and the areas contain high-priority loads like emergency hospitals (mainly ICUs, ventilators, surgical units), emergency services, street lights, railways, airport services, and critical household loads (refrigerators, water pumps, and heating or cooling systems). The current energy crisis is due to the high dependence on non-renewable energy sources (coal, gas, and oil), which is one of the main factors hindering economic development, human comfort, and national stability [1]. There is a growing worry that these sources are both expensive and polluting, and are being depleted, and their costs continue to escalate, making them a less and less reliable source of energy [2][3]. One commonly proposed solution to prevent load shedding in developing countries is the construction of non-renewable energy generation plants. Although common, this method is very expensive and inefficient when applied on a large scale over a long period of time [4]. One way is to use batteries for storage. However, battery-based energy storage systems are costly and may become inefficient due to installation costs, maintenance requirements, and limited storage capacity [5]. These constraints have spurred the researchers and engineers to find more efficient and environmentally sustainable solutions for energy management. Over the past few years, considerable efforts have been devoted to utilizing machine learning and deep learning methods to address energy forecasting and management problems. In recent years, there has been substantial advancement in the application of machine learning and deep learning in addressing energy forecasting and management issues. Regarding renewable energy forecasting, [6] did a comparative study of ARIMA, SARIMA, and LSTM models for forecasting solar and wind energy generation and concluded that LSTM can predict more complex time series patterns than traditional statistical models. Likewise, the study described in [7] used several machine learning models for short-term forecasting of solar and wind energy in microgrids, and showed high prediction accuracy for various weather conditions. The work in [8] further demonstrates the advantages of LSTM over two other algorithms, Random Forest and XGBoost, for solar and wind forecasting, and also found that LSTM always outperforms the other two algorithms for time series forecasting of Renewable Energy. In the domain of load demand prediction, [9] employed an XGBoost model for the short-term electrical load forecasting, and obtained high accuracy by fusing the weather and historical consumption data as input features. The hybrid of Prophet-BO-XGBoost model was proposed in [10] for short-term load forecasting in power systems and revealed that the models based on XGBoost are efficient for electricity demand forecasting patterns. The results of these studies validate both LSTM and XGBoost as powerful and well-established tools for energy and load forecasting applications. In the field of smart grid energy management, research in [11] showed that AI and LSTM for forecasting have a direct impact on the efficiency of the smart grid by optimizing energy distribution decisions and minimizing operational expenses. In [12], it was also proved that bidirectional LSTM networks with an attention mechanism can achieve considerable accuracy in forecasting in the field of smart grid energy management systems. Most recently, the research in [13] proposed an AI-based smart grid optimization for optimization of renewable energy generation, predictive maintenance, and load forecasting based on an LSTM network in a hospital in Malaysia. But their efforts were only targeted to a single hospital building and were not city-wide energy management.

Research Gaps and Motivation:

Although considerable advances have been made in the field of energy forecasting using machine learning, there are still a number of important challenges that are not addressed in the literature. So far, most of the studies have addressed renewable energy forecasting or load demand forecasting, but not both simultaneously in a single forecasting system. Studies that focused on solar forecasting [14] did not take wind energy or load demand into account, and studies that focused on wind forecasting [15][16] did not include load management. The same applies to load forecasting studies [17][18][19], which did not include renewable energy generation in their models; they could only foresee a load but not the additional renewable energy load. Some researchers have studied energy management for smart grids for different facilities, e.g., a hospital in Malaysia [13] has developed an AI-based load management system which used LSTM based load forecasting and renewable energy integration in a single building, without any physical circuit modeling, and not considering city-wide priority-based load management in all load categories [20][21]. More recent research has also examined integrated approaches that integrate renewable energy forecasting with smart grid energy management for urban systems, including the approach of optimizing generation scheduling and policy regulation presented in [22]; however, such approaches do not incorporate explicit priority-based load classification to ensure the supply of uninterrupted power to critical loads. The present work fills this gap by introducing high-priority and low-priority load demand forecasting, explicit priority-based load classification, and also making the entire city energy management system with solar and wind energy forecasting, where all the high-priority loads in the entire city are always powered while minimizing the backup generator usage in the system, which has not been achieved in any existing study.

Research Objectives:

Design and implementation of a rule-based smart energy management system in MATLAB/Simulink.

To forecast solar and wind energy generation using LSTM networks and load demand using XGBoost.

To have an uninterrupted and continuous power supply to high-priority loads throughout the city under all operating conditions.

To reduce the need for activating backup generators by maximizing the use of renewable energy sources, thereby minimizing unnecessary operating costs and dependence on non-renewable energy sources.

Novel Contribution:

Unlike previous studies that addressed either forecasting or energy management in isolation and were limited to single facilities, this paper presents the unified framework that integrates LSTM-based renewable energy forecasting, XGBoost-based load demand forecasting, and priority-based rule-driven power distribution in a single system. The framework is validated through MATLAB/Simulink simulation and is specifically designed to address city-wide energy management in developing countries, facing frequent load shedding, a gap that no existing study has addressed.

Literature Review:

Forecasting the generation of renewable energy, particularly solar and wind energy, has become a popular application of machine learning techniques for improving prediction accuracy. The integration of these renewable sources into smart grids presents several challenges due to their intermittency and volatility, making accurate forecasting and efficient energy management difficult. Additionally, load forecasting is a crucial component in balancing energy supply and demand, which is essential for the smooth and efficient operation of smart energy systems. Researchers in [23] used deep learning techniques for the prediction of solar energy. They focus on a solar renewable energy source and also show how deep learning can provide accurate forecasting results. The integration of renewable energy into power will be improved. He does not include load forecasting, which is important for maintaining energy supply and load demand. Their study is limited because it only involves solar energy and does not mention other forms of renewable energy. [24] studied energy generation forecasting using machine learning techniques. They focus on the fact that a data-informed approach can be powerful to calculate the renewable source output, which helps to improve planning and minimize reliance on traditional energy sources. It does not study load forecasting, which is important for achieving reliability and maintaining energy management. [14]. They use advanced machine learning methods for solar irradiance forecasting for both short- term and long- term periods in Zafarana, Egypt. They use CNN and LSTM to understand the impact of different weather factors on solar energy production. Their approach reached strong results in solar forecasting. They do not focus on load forecasting. This is an important parameter for managing energy stability. [15] researched wind power forecasting using a variety of machine learning and deep learning models, including Random Forest, KNN, Decision Tree, MLP, and AdaBoost. Their findings showed that these techniques yield high accuracy even when extended over a year. However, they focused exclusively on wind power without mentioning load forecasting or how to manage the integration of multiple energy parameters. [16] compared the performance of nine machine learning models and four time-series models for wind energy prediction. They confirmed that LSTM and GRU models have the strongest ability to capture time-series patterns in wind data. Despite achieving high accuracy, their study does not incorporate load forecasting or address energy stability. The study in [XX] investigated energy load forecasting in green buildings using deep learning. They employed LSTM models to predict electricity loads based on temperature, humidity, and historical consumption data. While load forecasting is a critical parameter, their research does not account for renewable energy [20] worked on resilience-oriented optimization of hospital microgrids. Their study focused on maintaining critical loads during grid outages using solar power and Battery Energy Storage Systems (BESS). They demonstrated that priority-based energy dispatch could reduce energy shortages for critical loads by up to 63%. However, the scope was limited to solar energy and batteries, omitting other renewable sources such as wind. [21] worked on a hospital microgrid system designed to maintain high-priority loads for 24 hours. Their study focused on a solar and a diesel generator running in parallel and would provide a backup to critical loads during power cuts. The diesel was used in the worst case when the solar generation was low. The study mostly focused on solar energy. Diesel is strictly a backup, and not a primary source, of electricity. Another study compared the utilization of CNN-LSTM and CNN-GRU deep learning models for short-term load forecasting models and concluded that these models show a precise forecast, although the accuracy decreases with an increase in the forecasting horizon. They also did not consider the time period of renewable energy integration, nor simultaneous load forecasting, in their study of load forecasting in a smart grid. [19] Inspired by the observed structure, proposed a load prediction system based on Recurrent Neural Networks and long short-term memory units. The output was simulated using MATLAB/Simulink to identify patterns in both the load data and the weather from the past. The LSTM-RNN model of the author achieved an RMSE of 2.2889, an MAE of 1.104, and a MAPE of 1.538%. The author only did load demand forecasting and not renewable (solar and wind) energy forecasting. As generation forecasting is important for maintaining system security. [25] concluded that RES (wind and solar) integration into smart grids remains a challenge due to their random generation behavior. Accurate forecasting or prediction of renewable generation is needed for balancing and maintaining the reliability of the system. Load forecasting is not included in Nabil's work on solar and wind forecasting. A study was conducted on an AI-based smart grid framework designed for a tertiary hospital in Kuala Lumpur, Malaysia. The system integrates renewable energy generation, load forecasting, predictive maintenance, and HVAC energy management to enhance overall efficiency. An extensive analysis of the hospital's electrical system covering a built-up area of 158,305 m², 1,500 beds, and over 200 devices was performed to develop an appliance-level model reflecting both predictable and stochastic energy patterns. Advanced forecasting methods, specifically Long Short-Term Memory (LSTM) networks combined with Reinforcement Learning (RL), were employed to manage variable load demands, optimize renewable energy utilization, and reduce uncertainties arising from varying occupancy levels and equipment operations. They have developed their model for hospitals only. It is obvious that most studies related to renewable energy focus on solar and wind energy forecasting. Furthermore, while some work exists regarding smart grid systems for specific sections like hospitals, research on priority-based load management remains relatively limited and small in scale. Previous studies only used artificial intelligence and long short-term memory (LSTM) models for forecasting. We propose an improved energy management system, which is based on renewable energy forecasting that estimates available energy and load forecasting to predict and match demand. We use LSTM for generation forecasting and XGBoost for load demand forecasting. We also classify loads by their high-priority and low-priority levels , and high-priority loads are continuously supplied with power from the backup generator. The backup is only activated when available energy falls short. This improves system reliability and maintains cost-effectiveness.

Methodology:

In this project, the goal is to develop a machine learning model to forecast renewable (solar and wind) energy generation and load demands.

Data Collection:

In this study, we used four datasets that I have collected from publicly available sources, including Kaggle and the Figshare platform. The renewable energy datasets (solar and wind) were obtained from [26], while the load demand datasets were obtained from [27]. These four datasets are separately utilized, corresponding to solar generation, wind generation, low-priority demand, and high-priority load demand. The solar datasets include parameters like Total solar irradiance, Global horizontal irradiance, temperature, and atmospheric conditions, which are used to forecast the output power of a 130MW solar power plant. The dataset starts from Jan 2019 to Dec 2020 with a 15-minute time observation. The wind dataset includes parameters like wind speed, wind direction, Relative humidity, and other environmental parameters, which are used to forecast the power generation of a 200 MW wind power plant. This dataset also covers from Jan 2019 to Dec 2020 with 15-minute time observations. The load datasets consist of historical electricity demand data, such as Previous_Day_Consumption, Temperature, Humidity, etc., which are mostly weather parameters, and are divided into two categories: high-priority loads and low-priority loads. The high-priority load dataset represents essential services, while the low-priority load dataset represents flexible demand. Both datasets cover the period from Jan 2023 to Dec 2023 with a 15-minute sampling interval.

Data Preprocessing:

Data preprocessing is an essential step to ensure data quality, improve reliability, reduce errors, and improve model performance of the machine learning models. The collected datasets are processed through several stages, including handling missing values, normalization, and feature selection.

Missing Value Handling:

The datasets often contain missing, invalid, or incomplete records, which can reduce the performance of machine learning models. In this study, missing values are handled using a combination of techniques:

Missing values are handled using a suitable technique such as interpolation or previous value filling, depending on the nature of the data. This ensured that the dataset remains complete and consistent for further analysis.

Invalid entries such as -99, NaN, null, and empty values are first replaced with NaN.

A time-based interpolation method is applied to estimate missing values based on adjacent time steps.

Data Normalization:

Since the input variables contain features with different scales and ranges (e.g., temperature, relative humidity), normalization is applied to bring all features to a similar scale. The Min-Max scaling technique is used to transform all input features into a range of 0 and 1. The output variable is scaled separately to avoid bias.

The scaler is fitted only on the training data and then applied to the test data to prevent data leakage.

Normalization helps the machine learning models, particularly LSTM, to learn more efficiently and produce stable predictions.

Feature Selection:

Feature selection was performed to identify the most important input variables for renewable energy and load forecasting. Important features such as time-related parameters, historical generation values, and historical load values were selected because they have a strong influence on prediction accuracy. Irrelevant or redundant features were removed to reduce complexity and improve the efficiency of the forecasting models.

For renewable energy forecasting, the selected features include:

Solar irradiance parameters

Temperature

Atmospheric pressure

Relative humidity

Time-related variables

For load forecasting, the selected inputs include:

Time-based features such as hour, month, and day of the week

Weather-related parameters

Renewable energy generation values

Historical load consumption

Machine Learning Model Development:

In this study, we developed four machine learning models to predict renewable energy generation and load demand.

Solar generation forecasting (130 MW) using LSTM

Wind generation forecasting (200 MW) using LSTM

High-priority load forecasting using XGBoost

Low-priority load forecasting using XGBoost

The selection of LSTM and XGBoost models is based on their suitability for different data types and their comparative advantages over conventional models. LSTM is selected for renewable energy forecasting due to its capability to capture temporal dependencies in time-series data such as solar and wind energy generation. In contrast, XGBoost is selected for high-priority and low-priority load forecasting because it performs well on structured tabular data and provides high accuracy while reducing overfitting through boosting. Compared to traditional models such as linear regression, support vector machines, and decision trees, XGBoost provides better generalization. Therefore, the combination of LSTM and XGBoost provides efficient forecasting of both renewable energy generation and load demand.

Model Validation Strategy: The datasets are split into training and testing sets using an 80:20 ratio to ensure reliable evaluation. For LSTM-based renewable energy forecasting, a sliding window with a time step of 96 is used, and Min–Max normalization is performed after the split to avoid data leakage. Early stopping is used to avoid overfitting. Hyperparameters such as the number of neurons, the number of layers, learning rate, and batch size are tuned to improve model performance. For XGBoost-based load forecasting, time-series cross-validation (TimeSeriesSplit) is used to evaluate the model on sequential data. Hyperparameters such as the number of estimators and the learning rate are optimized to improve accuracy and generalization. Model performance is evaluated using MSE, RMSE, MAE, and R^2.

Model Architecture:

Solar and Wind Forecasting Model:

For solar and wind power prediction, an LSTM model was used because it works well with time-based data. The model has multiple LSTM layers followed by dropout layers to reduce overfitting. At the end, dense layers are used to give the final output.

Load Forecasting Model:

For load prediction, an XGBoost model was used. This model is good for handling structured data and finding patterns between different inputs. The model utilizes input features such as such as time (hour, month, day), weather conditions, renewable energy generation, and previous-day-load.

Workflow and Decision Rule for Load Management:

The complete workflow of renewable energy forecasting and priority-based load management is shown in Fig. 1, which presents the step-by-step process of the smart energy system.

The workflow starts with the collection of input datasets, including solar energy, wind energy, high-priority load, and low-priority load. These datasets are processed through data preprocessing, such as missing value handling, normalization and feature engineering, to ensure consistency and improve forecasting performance. After preprocessing, the system predicts outputs for high-priority load, low-priority load, wind power, and solar power. The system calculates the total output power of the renewable energy by integrating wind energy and solar energy. The total load is calculated by summing the high-priority load and low-priority load. The decision rules are as follows:

Case 1: Renewable Generation ≥ Total Load:

When total renewable energy generation (solar + wind) is greater than or equal to the total load demand, the high-priority load and low-priority load are supplied and the backup generator is switched OFF since enough renewable energy is available to satisfy the load demand.

Case 2: Renewable Generation < Total Load:

When the total renewable energy generation (solar + wind) is less than the total load demand, the low priority load is disconnected and the renewable energy is used to satisfy the high priority loads. The generator is not in operation. This step ensures that essential loads receive power first while reducing unnecessary demand on the system.

Case 3: Renewable Generation < High-Priority Load:

When the total renewable energy generation less than the high-priority load demand, the backup generator is automatically turned ON. The generator provides extra power to support essential high-priority loads. Low-priority loads remain disconnected to ensure system stability.

Finally, the system supplies this energy to the required load and displays the output, thereby completing the process of smart energy management to optimally utilize renewable energy, stabilize the system, and prioritize the required loads.

The complete workflow is shown in Figure 1:

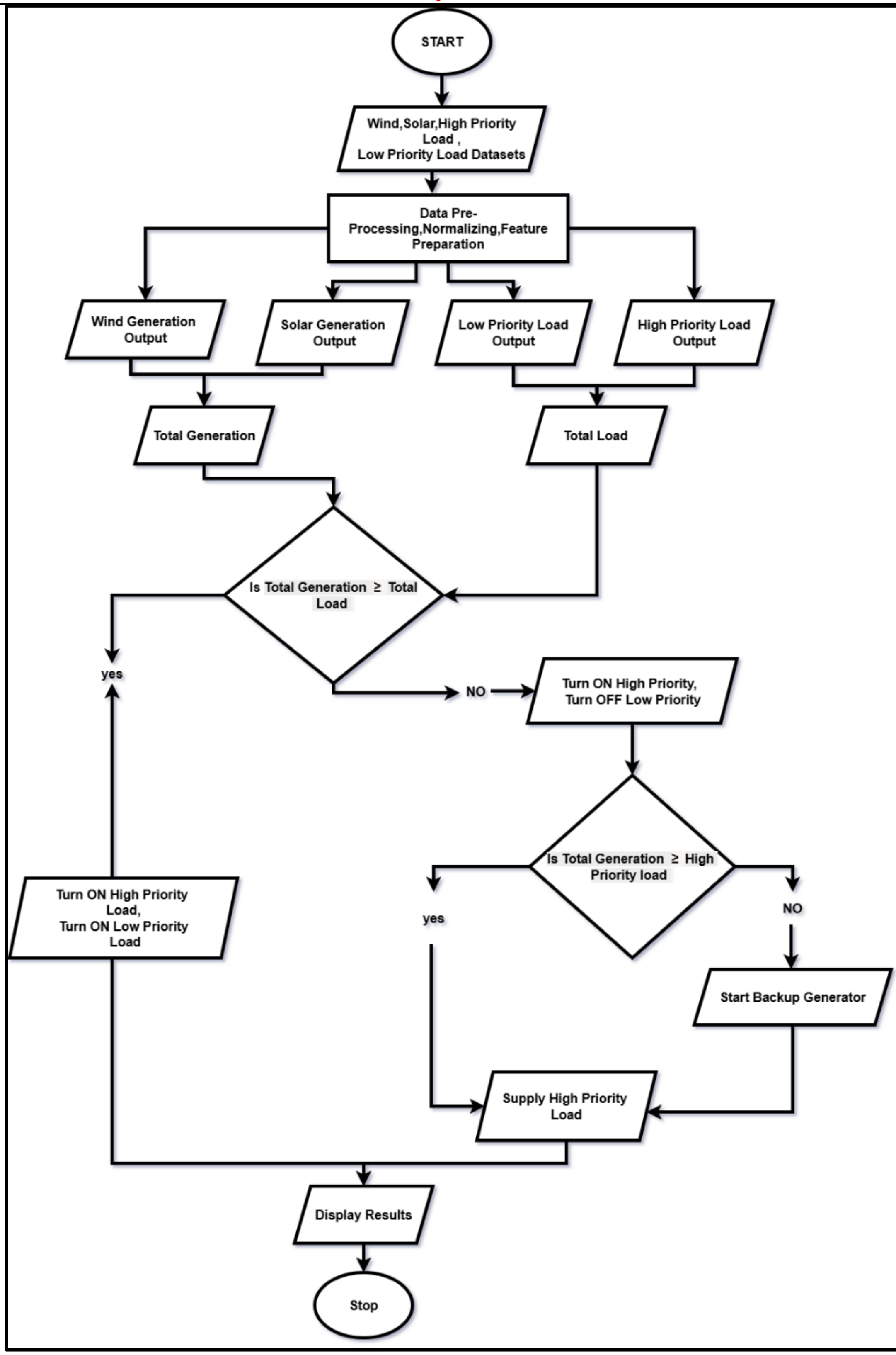

Figure 1. Workflow and decision process of the proposed smart energy management system.

MATLAB/Simulink Implementation:

The research for the smart grid energy management system is implemented in the MATLAB/Simulink environment in order to model the integration of renewable energy generation, load demand, and control decisions. The Simulink model consists of multiple interconnected blocks representing renewable generation forecasting, load forecasting, and the smart grid control system.

First, the predicted outputs from the machine learning models, including solar energy generation, wind energy generation, high-priority load, and low-priority load, are imported into Simulink using input blocks such as MATLAB Function blocks. Each dataset is imported through its respective “From Workspace” block. The datasets consist of values recorded at 15-minute intervals. The machine learning models process the datasets at 15-minute intervals, and the predicted values are updated dynamically to represent real-time system behavior.

The total renewable generation is calculated by combining solar and wind outputs through summation, while the total load is obtained by summing both load types. A rule-based control logic is implemented using relational and switch blocks to compare generation and demand.

A smart grid controller is implemented using logical operators, relational blocks, and switching mechanisms. The controller continuously compares total renewable energy generation with total load demand and makes control decisions based on predefined conditions. This Simulink implementation enables real-time simulation of the smart grid system.

The MATLAB/Simulink implementation of the proposed system is shown in Figure 2:

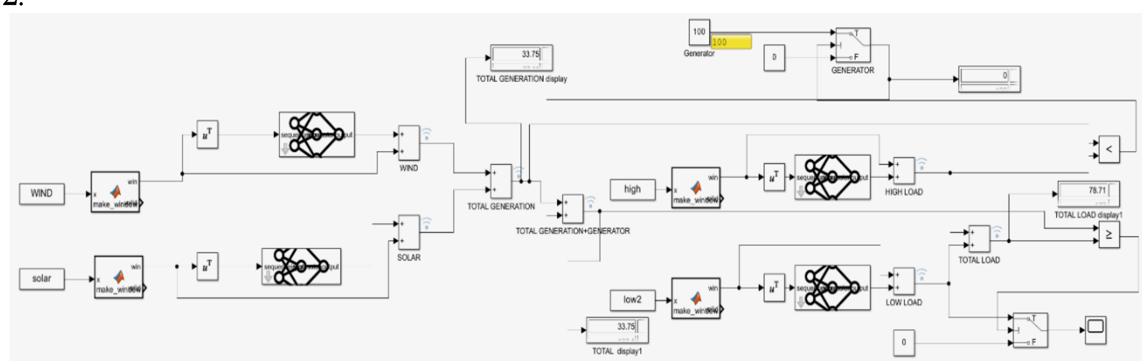

Figure 2. MATLAB/Simulink implementation of the proposed smart grid energy management system.

Result and Discussion:

Case 1: Renewable Generation ≥ Total Load:

Table 1 and Figure 3 present the results of the smart grid simulation under high renewable energy conditions. The data in Table 1 shows that the combined solar and wind generation is higher than the total load demand, indicating that the system can operate entirely using renewable energy sources. This operating behavior is illustrated in Figure 3, where each point represents a 15-minute interval. For most of the time intervals, the available generation is sufficient to supply both high-priority and low-priority loads; therefore, the backup generator remains OFF. However, at a few instances, the generation falls below the total load demand. In such situations, the system supplies only the high-priority load and disconnects the low-priority load to maintain system balance.

Overall, the results demonstrate that renewable energy is sufficient to meet the load demand and maintain stable system operation without relying significantly on backup generation.

This behavior verifies that the proposed system effectively achieves Objective (smart energy management) and Objective (reduced generator usage) by fully utilizing renewable energy whenever it is available.

Table 1. Smart Grid Simulation Results under High Renewable Generation.

Time	Solar Power (MW)	Wind Power (MW)	Total Generation (MW)	High Priority Load (MW)	Low Priority Load ON (MW)	Low Priority Load OFF (MW)	Total Load (MW)	Generator Output (MW)
1	80.92	101.8	182.7	39.67	134.5	0	174.2	0
2	77.37	125.8	203.1	22.75	75.28	0	98.03	0
3	71.67	143.3	215	36.71	124.2	0	160.9	0
4	63.17	138.2	201.3	36.08	121.9	0	158	0
5	34.25	113.8	148	17.16	55.74	0	72.9	0
6	34.57	100.3	134.9	35.51	0	120	155.5	0
7	36.32	118.4	154.7	7.006	20.2	0	27.2	0
8	21.35	143.1	164.5	27.14	90.66	0	117.8	0
9	15.94	149.5	165.4	13.95	44.51	0	58.47	0
10	12.03	151.3	163.4	10.01	30.73	0	40.74	0

Table 2. Smart Grid Simulation Results under Low Renewable Generation.

Time	Solar (MW)	Wind (MW)	Total Generation (MW)	High Priority Load (MW)	Low Priority Load ON (MW)	Low Priority Load OFF (MW)	Total Load (MW)	Generator (MW)
1	0.2965	43.95	44.24	26.04	0	91.11	117.2	0
2	0.2965	35.08	35.37	9.038	0	31.59	40.63	0
3	0.2965	41.41	41.7	14.53	0	50.83	65.36	0
4	0.2965	41.1	41.39	17.21	0	60.18	77.38	0
5	0.2965	36.91	37.2	20.43	0	71.48	91.92	0
6	0.2965	36.21	36.5	32.28	0	112.9	145.2	0
7	0.2965	25.65	25.94	11.2	0	39.18	50.38	0
8	0.2865	22.71	22.99	22.53	0	78.81	101.3	0
9	0.2865	25.48	25.76	25.34	0	88.66	114	0
10	0.2965	16.22	16.51	5.689	0	19.87	25.56	0

Table 3. Smart Grid Simulation Results Under Insufficient Renewable Generation Using Backup Generator

Time	Solar Power (MW)	Wind Power (MW)	Total Generation (MW)	High Priority Load (MW)	Low Priority Load ON (MW)	Low Priority Load OFF (MW)	Total Load (MW)	Generator Output (MW)
1	0.5338	0.01646	0.5503	14.36	46	46	60.36	100
2	0.5338	0.01646	0.5503	6.097	17.08	17.08	23.18	100
3	0.5338	0.01646	0.5503	22.53	74.59	74.59	97.11	100
4	0.5438	0.01646	0.5603	16.5	53.48	53.48	69.98	100
5	0.5338	0.01646	0.5503	27.19	0	90.91	118.1	100
6	0.5338	0.01646	0.5503	16.35	52.97	52.97	69.32	100
7	0.5338	0.01646	0.5503	16.45	53.31	53.31	69.76	100
8	0.5438	0.01646	0.5603	32.41	0	109.2	141.6	100
9	0.5338	0.01646	0.5503	7.384	21.59	21.59	28.97	100
10	0.5338	0.01646	0.5503	38.15	0	129.3	167.4	100

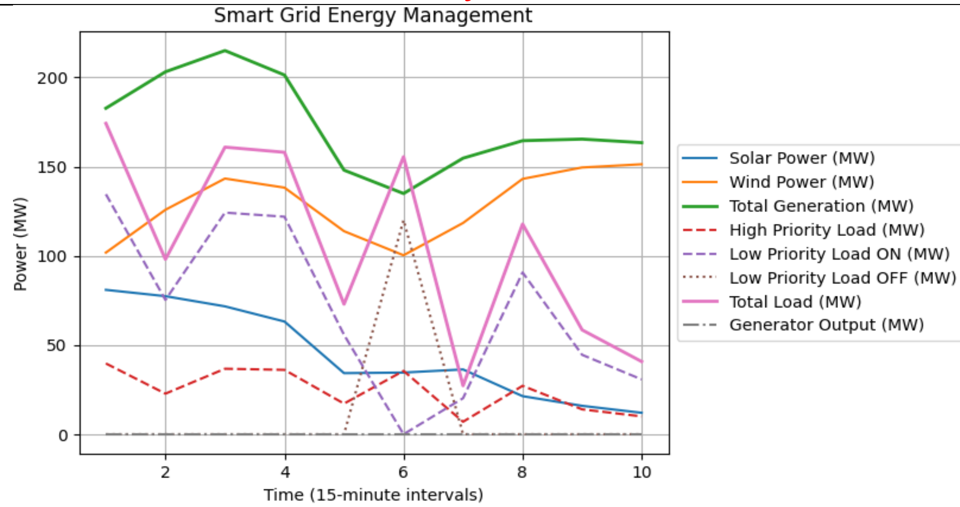

Figure 3. Smart Grid Energy Management under High Renewable Generation.

Case 2: Renewable Generation < Total Load:

Figure 4 and Table 2 present the smart grid simulation results under low renewable generation conditions. As shown in both Figure 4 and Table 2, the total renewable generation is significantly lower than the total load demand. Since the available generation is insufficient to meet the entire load demand, the low-priority load is disconnected, while the available renewable energy is used to supply only the high-priority loads. This means that generation is sufficient to supply the high-priority load demand, and the low-priority load is OFF (disconnected from the system). In this situation, the backup generator remains off and the system operates only on renewable energy. This approach limits the dependency on non-renewable energy sources and lowers the overall cost of maintaining supply to loads.

This outcome directly supports:

Objective (priority-based load forecasting)

Objective (ensuring continuous supply to critical loads

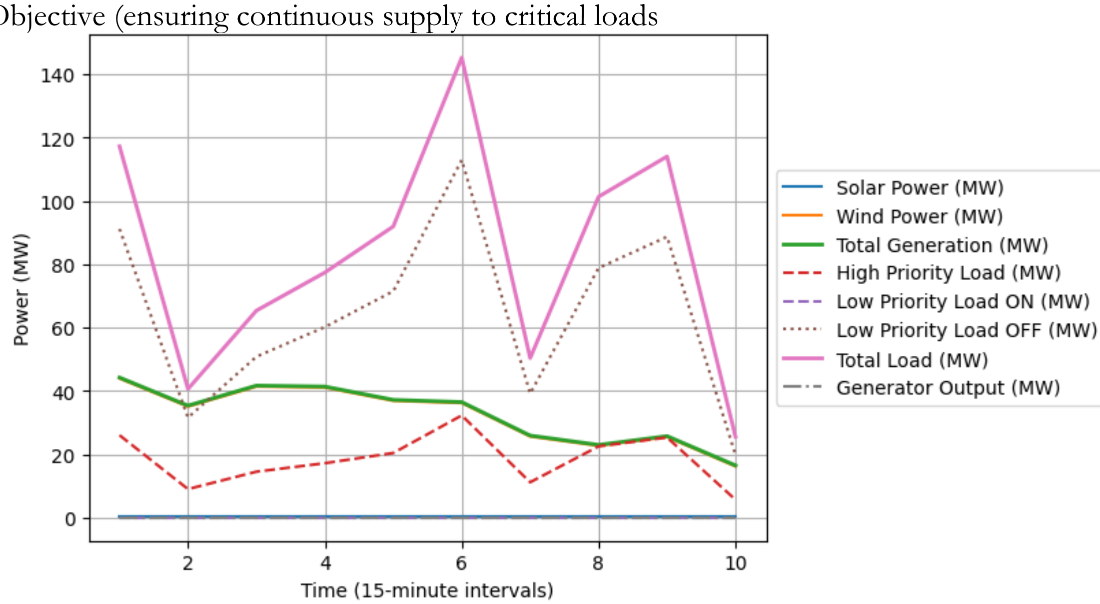

Figure 4. Smart Energy Management under Low Renewable Generation.

Case 3: Renewable Generation < High-Priority Load:

In Table 3 and Figure 5, the smart grid simulation result under insufficient renewable generation using backup generator are shown. As shown in Table 3, the solar and wind generation output is lower than the total load. In this condition, the total renewable generation is insufficient for the total load demand; however, the high-priority load demand exceeds the total renewable generation. The generator is automatically turned on and ensures that the power supply is maintained for the high-priority load. The generator is activated to maintain system stability.

If the combined output of solar and wind generation, along with the generator output, is greater than total demand, then power is supplied to both high-priority and low-priority loads. However, if the total power remains lower than the demand, the system continues to supply power to high-priority loads while low-priority loads are disconnected. In Figure 5, each time step represents a 15-minute interval.

This verifies that:

Objective (continuous supply) is successfully attained.

Objective (regulated generator usage) is maintained, as the generator is only used when necessary

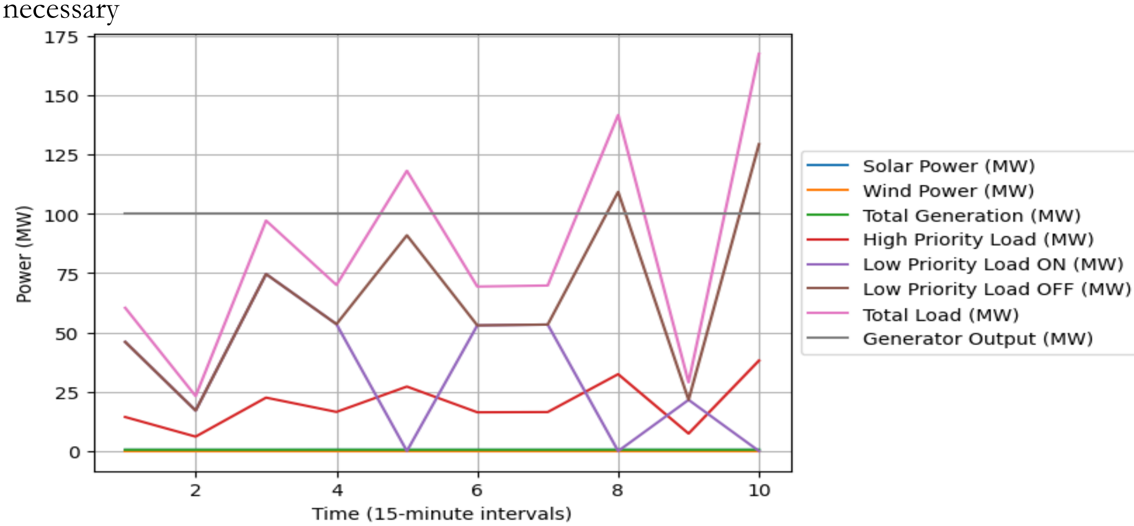

Figure 5. Smart Grid Simulation Results Under Insufficient Renewable Generation Using Backup Generator.

Performance Evaluation:

Load Demand Prediction Performance (High and Low Priority Loads):

The performance of the high-priority and low-priority load models was determined by comparing the predicted values with the actual load demand over a few days. The predicted load graph closely follows the actual load pattern, as shown in Figure 6. The graphical analysis shows a strong relationship between the actual and predicted values during both off-peak and peak periods. The high-priority load model achieved an R^2 score of 0.9007 (MSE =10.32, RMSE = 3.21, MAE=2.61), while the low-priority load model attained an R^2 score of 0.9004 (MSE = 126.78, RMSE = 11.26, MAE = 9.13), as shown in Table 4. These results show that the models explain approximately 90% of the variation in load demand and provide good predictive performance. To verify the model further, a single test sample was examined. For this sample, the actual power consumption was 133.16 MWh, while the predicted power value was 126.22 MWh. This small prediction error confirms that the model can predict load demand with acceptable accuracy.

Table 4. Performance Evaluation Metrics for Solar, Wind, and Load Prediction Models.

Model	Test MSE	Test RMSE	Test MAE	R^2 Score
Solar Generation	29.72	5.45	2.75	0.9577
Wind Generation	143.20	11.97	7.83	0.9537
High Priority Load	10.32	3.21	2.61	0.9007
Low Priority Load	126.78	11.26	9.13	0.9004

Obtain (Objective) Load Forecasting using XGBoost:

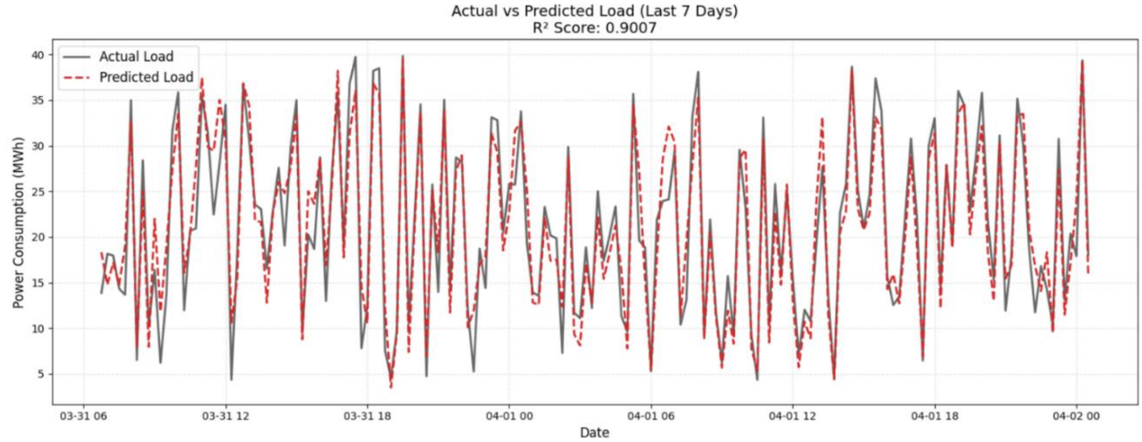

Figure 6. Load Demand Prediction Performance.

Generation Prediction Performance (Solar and Wind):

The performance of wind generation and solar generation is determined by comparing the predicted values with the actual generation over 299 time steps. The predicted generation graph closely follows the actual generation graph. The graph shows a strong relationship between the actual and predicted values during both off-peak and peak periods, as shown in Figure 7. The solar generation model achieves an R^2 score of 0.9576(RMSE=5.45, MAE=2.75, MSE=29.72), while the wind generation model achieves an R^2 score of 0.9536 (RMSE = 11.97, MAE = 7.83, MSE = 143.20), as shown in Table 4. These results show that the models explain approximately 95% of the variation in the total generation of renewable energy and show strong predictive performance. To verify the model further, individual test samples were examined. For one sample, the predicted power value was 74.97 MW, while the actual generation was 80.22 MW, resulting in a small prediction error, where each time step represents a 15-minute interval.

Obtain (Objective) generation Forecasting using LSTM:

These results confirm that the model effectively learns nonlinear and dynamics patterns in renewable energy generation, successfully achieving Objective

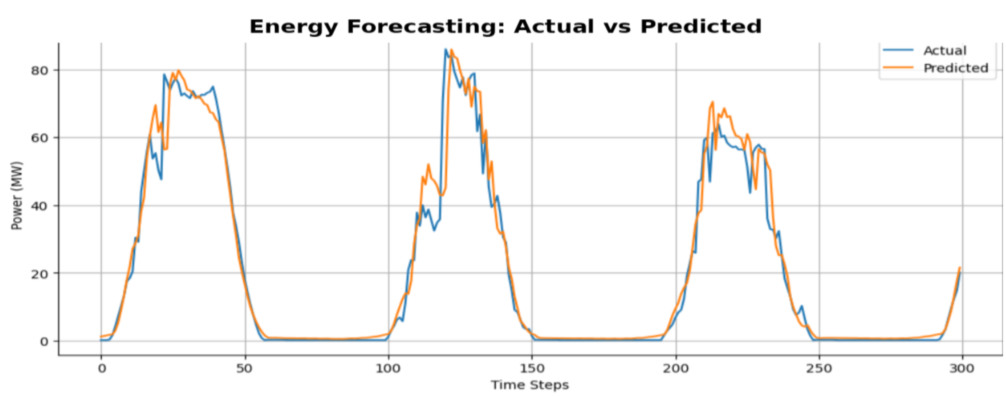

Figure 7. Generation Prediction Performance (Solar and Wind).

Comparison:

The obtained results show steady improvement over previous methods across all modules. For solar generation forecasting, the proposed model decreased RMSE from 20.1 to 5.45, MSE from 45 to 29.72, and MAE from 15.2 to 2.75, while increasing the R^2 score from 0.94 to 0.9577. For wind generation forecasting, RMSE reduced from 20.1 to 11.97, MAE from 15.2 to 7.83, MSE from 180 to 143.20, and R^2 score improved from 0.94 to 0.9537 [28], indicating better handling of complex renewable behavior. For load forecasting, the XGBoost model also exhibited better performance. In low-priority load prediction, R^2 score improved from 0.86 to 0.9004, MSE reduced from 130 to 126.78, RMSE from 13 to 11.26, and MAE from 13 to 9.13. For high-priority load prediction, RMSE decreased from 7.48 to 3.21, MSE from 56.72 to 10.32, MAE from 5.90 to 2.61, and R^2 score increased from 0.85 to 0.9007, [29] demonstrating improved modeling of demand fluctuations and load categorization.

Implications of the Study:

This proposed smart grid power management system has three types of impact: practical, commercial and social. From a practical standpoint, generating renewables and their load demand can be better predicted, which increases the reliability and stability of the smart grid in varying situations. From a commercial perspective, the proposed system enables more optimal electricity dispatch and reduces operational costs by minimizing standby diesel generator usage. It also improves the utilization of intermittent renewable resources and enhances energy security for hospitals and emergency services. In addition, it can contribute to sustainability by reducing dependency on non-renewable energy sources, reducing greenhouse gas emissions, and developing efficient and sustainable smart grid systems.

Future Work:

In future work, the smart grid energy management system can be improved by integrating more renewable energy sources such as biomass energy and hydroelectric energy into the smart grid to achieve more reliability and flexibility in the energy management system. The work may also be extended to reinforcement learning and advanced deep learning techniques for power prediction and optimization in real-time. Battery energy storage systems can help reduce the need for back-up generators while cybersecurity and fault detection technologies protect the smart grid and ensure reliable operation.

Conclusion:

The energy efficient smart grid energy management system achieved energy-efficient decisions through the proposed machine learning algorithms, where the solar and wind generation is being predicted for future time using the trained LSTM model. The high-priority and low-priority load demand is predicted using the XGBoost model which is sufficient to achieve effective real-time energy management decisions. This method can handle both high-priority and low-priority load demands because it ensures that all required loads (especially high priority loads) can be supplied in all possible situations, thus minimizing the amount of unimportant load shedding, and increasing the system's stability. The results of the simulation validate the ability of the proposed system to operate under varying levels of renewable generation, high and low priority loads and low generation levels. Furthermore, the system can minimize non-renewable generation and cost of operation while fulfilling continuous 24-hour power demand for high priority loads.

In general, it can be concluded that the advanced structure proposed in this paper is reliable, low-cost, and suitable for the needs of the new smart grid. The proposed structure will show the capabilities of machine learning methods to take advantage of renewable energies to stabilize the grid and save energy for the smart future cities.

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