Intelligent Machine Learning Framework for Renewable Energy Demand Forecasting

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ABSTRACT

The present study developed a Machine Learning-Based Energy Load Prediction and Management framework for Hybrid Renewable Energy Systems (HRES) to address the challenges of renewable energy uncertainty, dynamic load variations, and efficient power utilization. The proposed approach integrated renewable energy sources, energy storage systems, and intelligent machine learning-based forecasting techniques to improve system reliability and sustainability. Historical energy consumption data, renewable generation parameters, and environmental factors such as solar irradiance, wind speed, temperature, humidity, battery state of charge, and previous load demand were used for developing predictive models. Data preprocessing techniques, including normalization, noise reduction, missing value handling, and feature scaling, were applied to enhance data quality and improve model performance. Various machine learning algorithms, including Linear Regression, Random Forest, Decision Tree, and Support Vector Regression, were implemented and evaluated using performance indicators such as MAE, RMSE, and R^2 score. The results showed that Linear Regression achieved the highest forecasting accuracy with an R^2 score of 0.877, MAE of 16.255, and RMSE of 20.131, making it the most effective model among the evaluated techniques. The predicted energy demand was further integrated into an intelligent energy management strategy for optimizing renewable energy utilization, battery charging-discharging operations, and power distribution. The developed system improved energy efficiency, reduced energy wastage, minimized dependency on conventional power sources, and enhanced the stability of hybrid renewable energy systems. The proposed framework provides an effective solution for smart grid, microgrid, and sustainable energy management applications.

Keywords: *Machine Learning, Hybrid Renewable Energy System, Energy Load Prediction.*

1. INTRODUCTION

The rapid growth in global energy demand, depletion of conventional fossil fuel resources, and increasing environmental concerns have encouraged the development of sustainable renewable energy technologies. Traditional energy generation methods based on coal, petroleum, and natural gas contribute significantly to greenhouse gas emissions and environmental degradation. Therefore, renewable energy sources such as solar photovoltaic, wind, and other clean energy technologies have gained considerable importance for achieving sustainable energy development. However, renewable energy generation is highly dependent on climatic and environmental conditions, making its output uncertain and variable. Due to this intermittent nature, accurate energy forecasting and intelligent management strategies are required to ensure stable and efficient operation of renewable energy systems. Hybrid Renewable Energy Systems (HRES) have emerged as an effective solution for improving the reliability and performance of renewable power generation. These systems combine multiple renewable energy sources, energy storage technologies, backup generation units, and grid-support mechanisms to maintain continuous power supply. A typical hybrid system may include solar photovoltaic panels, wind turbines, battery energy storage systems, and intelligent control units. Through integrating different energy sources, fluctuations from individual renewable resources can be compensated, resulting in improved reliability and energy efficiency. However, managing energy balance, dynamic load variations, and unpredictable renewable generation remains a major challenge in hybrid renewable energy applications.

Conventional energy forecasting techniques, including statistical models such as regression analysis, autoregressive methods, and moving average approaches, often fail to accurately represent the complex and nonlinear characteristics of modern renewable energy systems. Machine Learning (ML) techniques provide advanced solutions by analysing large volumes of historical and real-time data to identify hidden patterns and relationships. Machine learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) have demonstrated significant potential in predicting energy demand and renewable energy generation with improved accuracy. Machine learning-based energy load prediction plays an important role in developing intelligent energy management systems. Accurate forecasting of future energy demand enables better scheduling of renewable energy resources, efficient battery utilization, reduction of energy wastage, and improved operational stability. Through continuously analysing information related to electricity consumption, weather conditions, renewable energy output, and storage status, ML models can support automatic decision-making and adaptive control. These capabilities help reduce dependency on fossil fuel-based backup systems and improve the overall sustainability of hybrid renewable energy networks.

The integration of machine learning with smart grid technologies has further enhanced the effectiveness of renewable energy management. Smart grids generate large amounts of operational data through advanced sensors, smart meters, and communication networks. This data provides valuable information regarding load demand patterns, weather variations, voltage conditions, and power generation trends. Machine learning algorithms utilize this information for demand forecasting, fault detection, energy optimization, and grid stability improvement. Consequently, ML-driven smart energy systems improve flexibility, reliability, and efficiency in modern power networks. Energy storage management is another important area where machine learning contributes significantly. Batteries and other storage devices maintain the balance between renewable energy generation and consumer demand. Improper storage operation may result in reduced battery life, power instability, and increased operational costs. Machine learning-based predictive control techniques optimize charging and discharging cycles by forecasting future energy availability and consumption patterns. This improves battery performance, enhances energy utilization, and ensures uninterrupted power delivery. Furthermore, machine learning models support the optimization and economic planning of hybrid renewable energy systems. Through combining ML techniques with optimization algorithms, researchers can determine suitable system configurations, component sizing, and operational strategies. These intelligent approaches help achieve cost-effective, reliable, and environmentally sustainable energy solutions. Therefore, machine learning-based energy load prediction and management provides an effective framework for addressing the challenges associated with renewable energy uncertainty and dynamic power demand. The present study focuses on developing an intelligent ML-based approach for accurate energy load prediction and efficient management of hybrid renewable energy systems to enhance system reliability, energy efficiency, and sustainable power utilization.

2. LITERATURE REVIEW

Ziyadanoğulları (2026) provided a comprehensive review of deep learning applications in renewable energy systems. The study highlighted the challenges associated with solar and wind power uncertainty, energy forecasting, microgrid management, fault detection, and predictive maintenance. Deep learning models such as CNN, RNN, LSTM, and GRU demonstrated superior performance. The study also discussed emerging concepts including explainable AI, physics-informed learning, and generative models while identifying challenges related to computational cost, data quality, and model generalization.

Ghaziasgar et al. (2025) investigated the importance of energy demand prediction in designing efficient hybrid renewable energy systems. The study developed a data-driven forecasting approach using previous weather conditions to predict building energy consumption. The RNN model achieved an R^2 value of 0.85 and MSE of 7.947. Integration with HOMER PRO improved system design, resulting in enhanced energy efficiency and additional green hydrogen production.

Parizad et al. (2024) examined the challenges of household energy systems, including increasing energy costs, peak load issues, and grid reliability concerns. The study emphasized the role of renewable energy integration, storage systems, and accurate forecasting techniques for effective energy management. A hybrid machine learning model developed using one year of data showed better performance than conventional methods with improved RMSE, MAE, and R^2 values.

Mirjalili et al. (2023) explored intelligent energy management solutions by integrating buildings, electric vehicles, and renewable energy sources into a controlled sustainable system. The study developed a neighbourhood energy model with solar-powered buildings and electric vehicles. Machine learning algorithms, including KNN, SVR, AdaBoost, and DNN, were applied for prediction. Results showed that DNN and KNN achieved higher forecasting accuracy based on RMSE evaluation.

Vlasov et al. (2022) studied the integration of renewable energy sources into existing power systems and addressed challenges related to energy mismatch and peak load conditions. The researchers proposed a predictive control framework using machine learning algorithms for hybrid energy systems containing solar panels, wind turbines, hydrogen generators, and conventional generators. The developed approach improved system reliability, resilience, and operational performance compared with traditional energy supply methods.

Rahman et al. (2021) presented an extensive analysis of machine learning-based time-series forecasting methods, particularly focusing on artificial neural networks for renewable energy applications. The study emphasized the limitations of fossil fuel resources and the importance of hybrid renewable energy systems for remote areas. Different ANN structures, including MLP, RNN, CNN, and LSTM, were evaluated for accurate energy forecasting under variable renewable conditions.

3. RESEARCH METHODOLOGY

3.1 Introduction and Research Framework

The research methodology defines the systematic approach followed for the development of a machine learning-based energy load prediction and management framework for Hybrid Renewable Energy Systems (HRES). The primary objective of this methodology is to design an intelligent adaptive system capable of forecasting future energy demand and optimizing renewable energy utilization under varying environmental conditions. The proposed methodology integrates data acquisition, preprocessing, feature extraction, machine learning model development, prediction analysis, performance evaluation, and intelligent energy management strategies. The research process begins with identifying the challenges associated with renewable energy intermittency and dynamic load variations. A data-driven approach is adopted where historical energy consumption patterns, renewable energy generation parameters, and environmental conditions are analysed to develop accurate forecasting models. The developed machine learning framework enables efficient energy scheduling, improved battery management, and reduced dependency on conventional energy sources. The complete research workflow includes dataset preparation, selection of significant input parameters, model training, testing, forecasting, and decision-making mechanisms for real-time energy management applications. This systematic methodology ensures that the proposed HRES operates efficiently while maintaining reliability, stability, and cost-effectiveness.

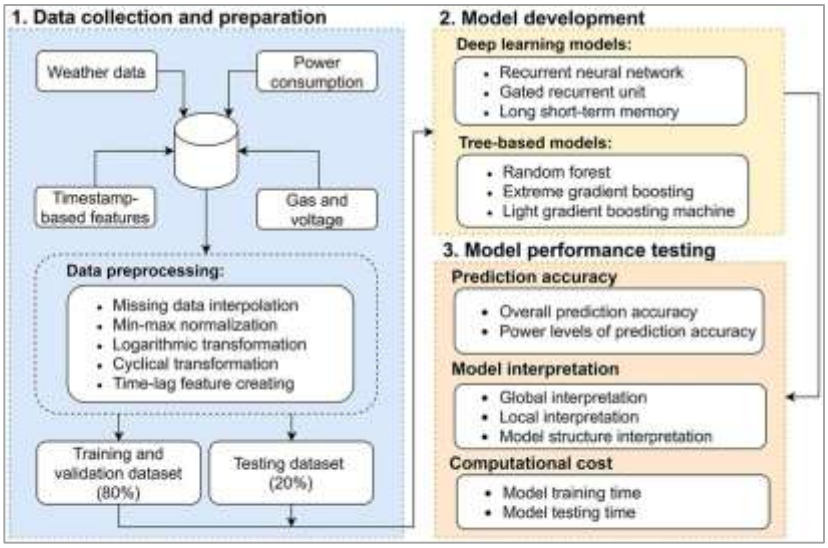

Figure 1: Development Process for Energy Prediction

The research follows a quantitative and simulation-based design approach for evaluating the performance of machine learning algorithms in hybrid renewable energy applications. Historical renewable energy and load demand datasets are collected from monitoring systems, sensors, smart meters, and environmental measurement devices. The collected data includes important parameters such as solar irradiance, wind speed, temperature, humidity, battery state of charge (SOC), and previous load demand. These parameters significantly influence renewable energy generation and consumer electricity requirements. Before applying machine learning models, the collected datasets undergo preprocessing operations such as removal of missing values, elimination of abnormal observations, noise reduction, normalization, and feature scaling. Feature selection is performed to identify the most influential variables affecting energy load prediction accuracy. Parameters such as previous load demand, solar irradiance, temperature, and renewable energy availability are selected as important predictive features. Additional characteristics such as seasonal variations, peak demand periods, and weekday/weekend consumption patterns are also considered to improve forecasting performance.

3.2 Proposed System Configuration and Data Processing Methodology

The proposed Hybrid Renewable Energy System consists of multiple integrated components including solar photovoltaic panels, wind turbines, battery storage systems, charge controllers, inverters, smart meters, and environmental sensors. Solar PV panels and wind turbines act as primary renewable energy generation sources, while battery storage provides backup support during low renewable energy availability. The charge controller regulates voltage and current flow between renewable sources and storage devices, whereas the inverter converts DC power into AC power suitable for consumer applications. Smart meters and sensors continuously monitor system parameters and provide real-time operational information for machine learning-based decision-making. The collected operational data is stored in structured formats such as CSV files for further analysis and model development.

The dataset used in this research contains renewable energy generation parameters and historical load demand information. Each sample consists of input variables including solar irradiance, wind speed, previous load demand, and corresponding energy load values. Solar irradiance represents solar radiation intensity available for photovoltaic generation, while wind speed indicates wind turbine operating conditions. Previous load demand provides historical consumption patterns that help machine learning algorithms identify future energy requirements. The energy load parameter represents the target output predicted by the developed models. Data preprocessing is an essential step because raw energy datasets may contain measurement errors, inconsistent values, and missing observations. The normalization process is applied to convert different parameters into a common range, improving model convergence and prediction accuracy. The normalized dataset is then divided into training and testing subsets, where 80% of the data is used for model training and 20% is used for performance evaluation.

3.3 Machine Learning Implementation and Evaluation Strategy

After preprocessing and feature selection, the prepared dataset is applied to machine learning algorithms for energy load prediction. The models learn the relationship between environmental parameters, renewable energy generation, and historical consumption patterns. During the training phase, machine learning algorithms adjust their internal parameters to minimize prediction errors and improve forecasting accuracy. The trained models are then evaluated using testing data to determine their effectiveness under unknown operating conditions. Performance evaluation is carried out using statistical measures such as prediction accuracy, error analysis, and comparison between actual and predicted energy loads. The best-performing model is selected based on its ability to provide accurate forecasts with minimum computational complexity.

The predicted energy demand obtained from machine learning models is further utilized for intelligent energy management. Based on forecasting results, the energy management controller determines the optimal distribution of available power among renewable sources, battery storage units, and grid support systems. The controller manages battery charging and discharging operations according to predicted generation and consumption patterns, preventing excessive energy loss and improving storage efficiency. Continuous monitoring enables the system to adapt according to changing weather conditions, load variations, and renewable energy availability. The proposed methodology therefore provides an intelligent solution for improving renewable energy utilization, reducing operational costs, enhancing system reliability, and supporting sustainable energy management. Through the integration of machine learning prediction and automated control strategies, the developed framework contributes to the advancement of efficient and reliable hybrid renewable energy systems.

4. RESULT AND DISCUSSION

The implementation of the Machine Learning-Based Energy Load Prediction and Management system for Hybrid Renewable Energy Systems (HRES) was carried out through a structured simulation framework involving data collection, preprocessing, feature extraction, machine learning model development, prediction analysis, and intelligent energy management. The proposed system integrates renewable energy sources such as solar photovoltaic and wind energy with battery storage and intelligent control mechanisms to achieve efficient power utilization. The complete workflow begins with defining system objectives, selecting suitable HRES components, collecting environmental and operational data, and preparing datasets for machine learning applications. The primary objective of this research was to accurately predict future energy demand and utilize the predicted information for optimal energy distribution. The developed framework considered important parameters including solar irradiance, wind speed, temperature, humidity, battery state of charge (SOC), and previous energy load. These parameters were processed and provided as input variables to different machine learning models. The models learned the relationship between renewable energy availability and load demand patterns, enabling accurate forecasting and improved energy management decisions.

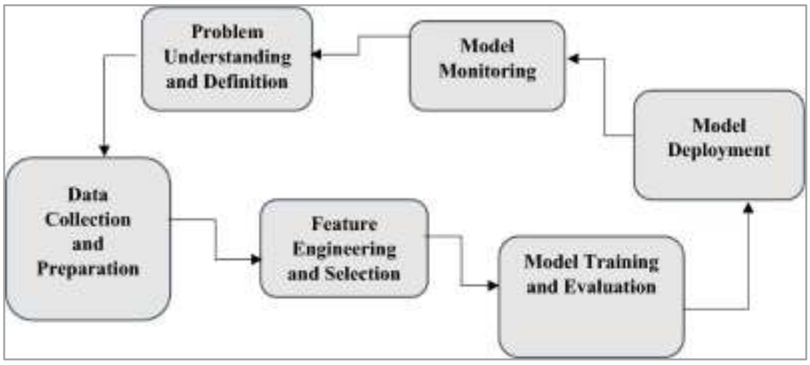

Figure 2: Development Workflow

The collected dataset was processed through various preprocessing techniques to improve the reliability and accuracy of machine learning predictions. Missing data handling, noise reduction, outlier detection, normalization, and feature scaling were performed before model implementation. Feature selection analysis identified previous load demand as the most influential parameter, followed by solar irradiance, temperature, wind speed, humidity, and battery SOC. The prepared dataset was divided into training and testing subsets, where the training dataset was used for model learning and the testing dataset was applied for performance evaluation. Several machine learning algorithms, including Linear Regression (LR), Decision Tree (DT), Random Forest (RF), and Support Vector Regression (SVR), were implemented for energy load prediction. The prediction capability of each model was evaluated using statistical performance indicators such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2 score). The obtained results demonstrated significant differences among the implemented models. Linear Regression achieved the best performance with the lowest MAE value of 16.255, RMSE value of 20.131, and highest R^2 score of 0.877. Random Forest also showed effective forecasting capability with an R^2 value of 0.830, whereas Decision Tree achieved moderate performance with an R^2 value of 0.743. SVR showed comparatively lower accuracy with an R^2 value of 0.396, indicating limited suitability for the given energy dataset.

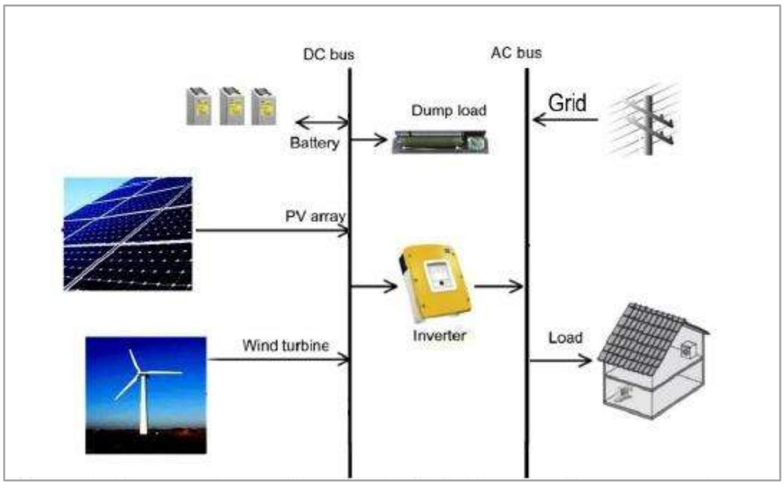

Figure 3: Hybrid Renewable Energy System Configuration

The comparative analysis confirmed that machine learning techniques can effectively predict energy load demand and support intelligent decision-making in hybrid renewable energy systems. Among all evaluated models, Linear Regression was selected as the optimal forecasting model due to its superior accuracy and minimum prediction error. The predicted load values generated by the selected model were further utilized by the energy management controller to determine suitable power distribution strategies. The intelligent energy management system continuously compared renewable energy generation with predicted load demand to select appropriate operational actions. When renewable energy production exceeded the predicted demand, the system utilized available renewable power and simultaneously charged the battery storage system. In conditions where renewable generation was insufficient, battery support or grid assistance was activated to maintain continuous power supply. The simulation results showed that for a predicted load demand of 39.89 kW, with solar power generation of 250 kW, wind power generation of 80 kW, and battery SOC of 60%, the system decided to use renewable energy sources and charge the battery. This demonstrates the effectiveness of the proposed ML-based management strategy in maintaining energy balance and improving renewable energy utilization. Overall, the results indicate that machine learning-based load prediction significantly enhances forecasting accuracy, reduces energy wastage, improves battery management, and increases the reliability of hybrid renewable energy systems. The developed approach provides an efficient solution for future smart grids, microgrids, and sustainable energy management applications.

5. CONCLUSION

The present research successfully developed a Machine Learning-Based Energy Load Prediction and Management framework for Hybrid Renewable Energy Systems (HRES). The study addressed the major challenges associated with renewable energy intermittency, dynamic load variations, and efficient power management by integrating machine learning techniques with intelligent energy control strategies. The proposed approach utilized historical energy consumption data, renewable energy generation parameters, and environmental conditions to accurately predict future energy demand and optimize renewable energy utilization. The methodology included data collection, preprocessing, feature selection, machine learning model development, performance evaluation, and intelligent energy management implementation. The developed HRES framework incorporated solar photovoltaic systems, wind energy generation units, battery storage systems, smart meters, and monitoring sensors to ensure reliable and sustainable energy operation. Important input parameters such as solar irradiance, wind speed, temperature, humidity, battery state of charge, and previous load demand were considered for energy load forecasting. Data preprocessing techniques, including normalization, noise reduction, missing value handling, and feature scaling, improved the quality of input data and enhanced the prediction capability of machine learning models. The research demonstrated that accurate forecasting of energy demand plays a significant role in maintaining power balance, reducing energy wastage, and improving renewable energy penetration.

Different machine learning algorithms, including Linear Regression (LR), Random Forest (RF), Decision Tree (DT), and Support Vector Regression (SVR), were implemented and compared based on forecasting performance. The results showed that Linear Regression achieved the best prediction accuracy with an R^2 score of 0.877, MAE value of 16.255, and RMSE value of 20.131. Random Forest also provided effective forecasting performance with an R^2 value of 0.830, whereas Decision Tree and SVR showed comparatively lower prediction accuracy. The findings confirmed that machine learning models can effectively capture the relationship between renewable energy availability, environmental conditions, and energy consumption patterns. Among the evaluated models, Linear Regression was selected as the most suitable model due to its higher accuracy and lower prediction error. The predicted energy demand was further utilized by the intelligent energy management system to optimize power distribution among renewable sources, battery storage, and grid support. The developed control strategy successfully managed energy flow according to renewable power availability and load requirements. When renewable energy generation exceeded the predicted demand, the system utilized renewable power and charged the battery storage unit. During insufficient renewable generation, battery backup or grid support was activated to maintain continuous energy supply. The simulation results demonstrated that the proposed management approach improved energy utilization, enhanced battery operation, and maintained system stability under varying operating conditions.

Overall, the study concluded that machine learning-based energy load prediction provides an effective solution for improving the reliability, efficiency, and sustainability of hybrid renewable energy systems. The integration of forecasting models with intelligent energy management techniques reduces operational costs, minimizes dependency on conventional grid systems, and supports the development of smart grids and microgrid applications. The proposed framework can be further enhanced by incorporating advanced deep learning models such as LSTM, GRU, Transformer-based networks, and reinforcement learning techniques for large-scale renewable energy systems. Future research may also focus on real-time implementation, cybersecurity improvement, and integration with electric vehicle charging infrastructure to develop more adaptive and intelligent sustainable energy management solutions.

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