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Predictive Modelling with Machine Learning for Sustainable Hybrid Energy System

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Abstract
In order to achieve sustainability and energy efficiency, hybrid energy systems must incorporate renewable energy sources. In order to maximize the performance of hybrid sustainable energy systems, this study investigates the use of machine learning (ML) approaches in predictive modelling. The study combines advanced machine learning (ML) methods like random forests (RF), support vector machines (SVM), and artificial neural networks (ANN) to forecast energy generation, demand, and system efficiency. These models improve grid stability, lessen dependency on fossil fuels, and improve energy management tactics by utilizing historical data. Through case studies, the suggested method is assessed and shown to be successful in forecasting energy outputs, allocating resources optimally, and reducing operating expenses. The results demonstrate how ML-driven predictive models can improve the sustainability and dependability of hybrid energy systems, assisting in the global shift to cleaner energy sources.

Keywords: *Sustainability, Renewable Energy, Hybrid Energy System, Machine Learning, Predictive Modeling.*

1. Introduction

A major movement towards renewable energy sources has been fueled by the growing demand for energy world- wide and the pressing need to safeguard the environment. Sustainable alternatives are crucial since conventional fossil fuel-based energy generation contributes to resource depletion, air pollution, and greenhouse gas emissions. Among the most promising renewable energy sources are solar and wind, which provide plentiful, affordable, and clean power options. However, grid stability and a steady supply of electricity are threatened by their sporadic nature. By balancing energy generation and consumption, hybrid energy systems—which integrate several renewable sources—offer a more dependable and effective option. To improve prediction accuracy and analyze complicated datasets, machine learning algorithms like support vector machines (SVM), artificial neural networks (ANN), and ensemble learning techniques will be investigated. The suggested strategy aims to solve the main obstacles to the integration of renewable energy, such as system efficiency, economic viability, and power generation variability. The results of this study will support sustainability and energy security in several areas by advancing intelligent energy management systems [1-3].

1.1. Challenges in Hybrid Renewable Energy Systems Unpredictability

Wind and solar power generation are impacted by weather conditions. Energy is either overproduced or underutilized as a result of poor forecasting. Limitations of Energy Storage: In order to store extra energy, effective battery management is necessary. Variations in energy supply and demand must be balanced. High Initial In- vestment Costs: Hybrid energy technologies require ex- pensive infrastructure. Energy allocation can be optimized via machine learning to lower operating expenses. Data Complexity: A number of variables, including temperature, wind speed, irradiance, humidity, and

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energy demand, affect how much energy is generated. Energy output is frequently not precisely predicted by current forecasting techniques [4].

1.2. Challenges in Hybrid Renewable Energy Systems Unpredictability

Machine learning is crucial to hybrid solar-wind energy systems because it improves energy forecasting, storage management, grid integration, cost optimization, and system efficiency. By analyzing weather data, historical energy trends, and present grid conditions, machine learning algorithms are able to predict energy generation with high accuracy. This reduces waste and boosts reliability. Additionally, machine learning enhances grid stability by reducing blackouts, optimizing electricity distribution, and balancing supply and demand. Predictive maintenance, efficient resource allocation, and intelligent energy trading all help to optimize costs and raise the economic feasibility of hybrid energy systems. ML automates decision- making and continuously learns from new data, enabling hybrid energy systems to operate more efficiently and adapt to environmental changes [5-8].

2. Literature Survey

Review of the Literature on Machine Learning for Solar- Wind Hybrid Energy Systems. Hybrid Energy System Optimization Making use of AI A common technique for improving the performance of hybrid solar-wind energy systems is machine learning. In order to ensure optimal energy distribution among solar panels, wind turbines, and battery storage, a hybrid deep learning model for real- time energy dispatch was presented in a study by Kumar et al. (2025). In order to anticipate operational problems and enhance long-term system reliability, Bashan et al. (2025) conducted more research on failure analysis in hybrid solar wind systems. They did this by utilizing fuzzy logic and AIbased decision-making models. Intelligent Energy Storage Control In hybrid energy systems, energy storage is essential, and machine learning has been used to improve storage effectiveness. An AIbased prediction model that dynamically modi- fies battery charging and discharging cycles based on current energy demand and meteorological conditions was created in a study by Song et al. (2025). According to Song et al. (2025), the results demonstrated that AI- driven battery management considerably increases battery life and lowers energy losses. In their investigation of hybrid AI models for energy storage optimization, Dewi et al. (2025) showed that integrating LSTM and random forest enhances battery management decision-making. Demand-Side Management and Grid Integration ML has also been used to enhance load balancing and grid integration in hybrid energy systems. In order to maximize energy dispatch in smart grids, decrease dependency on fossil fuels, and improve grid stability, Zhou et al. (2025) suggested a hybrid machine learning-based control system. Furthermore, Mchara et al. (2025) used wavelet and convolutional neural networks (CNN) to create a global irradiance prediction model. Their study demonstrated that more effective energy allocation in hybrid renewable energy systems is made possible by AI-powered predictive models (Mchara et al., 2025). 4. AI-Powered Trading and Cost Optimization for Renewable Energy Machine learning has been applied to energy trading and cost reduction as renewable energy markets develop. Using predictive pricing models, Kumawat et al. (2025) investigated AI-driven peer-to-peer (P2P) energy trading, in which pro- ducers and consumers trade excess renewable energy. According to their research, ML algorithms facilitate more sustainable energy transactions and increase the efficiency of the energy market (Kumawat et al., 2025). Tang et al. (2025) looked at cost-cutting measures and the economic feasibility of hybrid solar-wind systems in another study. According to the study, AI-based optimization techniques that maximize system performance while reducing energy production costs include Genetic techniques (GA) and Particle Swarm Optimization (PSO) (Tang et al., 2025). The research under consideration emphasize how important machine learning is for maximizing storage, incorporating hybrid energy systems into smart grids, cutting expenses, and enhancing system dependability. Combining deep learning,

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AI-based optimization methods, and hybrid machine learning models is turning out to be a game-changer for increasing the sustainability, economy, and efficiency of hybrid renewable energy systems.

3. Methodology

To guarantee precision and dependability in the findings, the study on Predictive Modelling using Machine Learning for a Sustainable Hybrid Energy System employs a systematic methodology. The following crucial steps make up the methodology, shown in Figure 1.

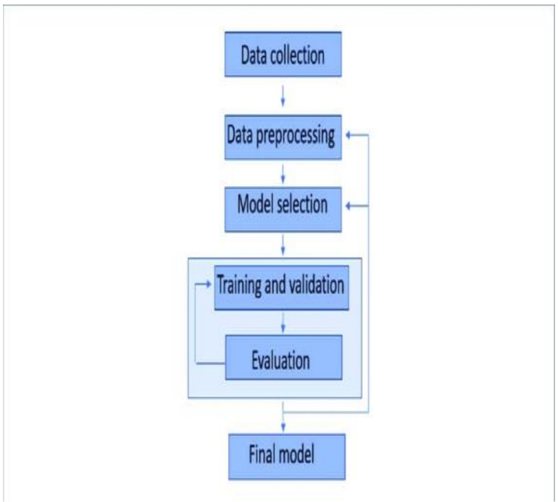
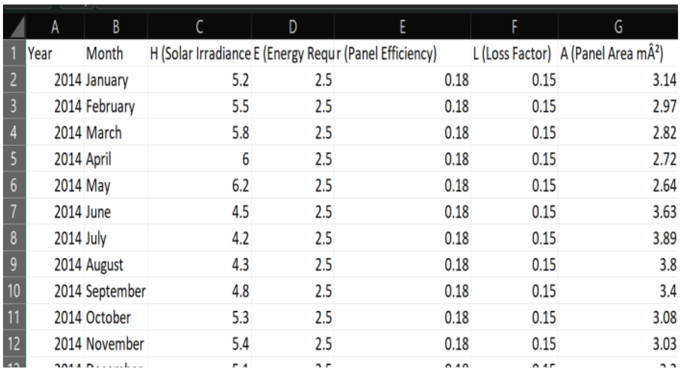


Figure 1 Machine Learning Flowchart

- **Data Collection:** Compile energy generation and consumption data in real time and in the past from a variety of renewable and non-renewable sources. Compile weather information, grid performance indicators, and hybrid energy system-related economic factors.
- **Preprocessing and Data Cleaning:** To guarantee consistency, handle missing values, eliminate outliers, and normalize data. Transform category variables into numerical representations so that machine learning algorithms can process them more effectively.
- **Feature Engineering and Selection:** Determine the critical factors influencing energy production and consumption. To produce significant features that raise predicted accuracy, apply statistical methods and domain expertise.
- **Model Selection and Training:** Select suitable machine learning models, including ensemble methods, decision trees, support vector machines (SVM), and artificial neural networks (ANNs). Use cross-validation techniques to verify performance after training models with historical data, shown in Figure 2.



Year	Month	H (Solar Irradiance	E (Energy Requr	(Panel Efficiency)	L (Loss Factor)	A (Panel Area mÂ²)
2014	January	5.2	2.5	0.18	0.15	3.14
2014	February	5.5	2.5	0.18	0.15	2.97
2014	March	5.8	2.5	0.18	0.15	2.82
2014	April	6	2.5	0.18	0.15	2.72
2014	May	6.2	2.5	0.18	0.15	2.64
2014	June	4.5	2.5	0.18	0.15	3.63
2014	July	4.2	2.5	0.18	0.15	3.89
2014	August	4.3	2.5	0.18	0.15	3.8
2014	September	4.8	2.5	0.18	0.15	3.4
2014	October	5.3	2.5	0.18	0.15	3.08
2014	November	5.4	2.5	0.18	0.15	3.03

Figure 2 Data Collection

- **Performance Evaluation:** Use metrics like R-squared values, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) to assess models. To find the most effective and precise forecasting model, compare various models.
- **Optimization and Integration:** Use methods such as grid search and hyperparameter tweaking to optimize model parameters. For in-the-moment decision-making, incorporate the prediction model into an energy management system.
- **Simulation and Validation:** Use software tools to simulate various hybrid energy situations. Compare the model's predictions with the system's actual performance.
- **Implementation and Suggestions for the Future:** Create a hybrid energy management decision-support system or prototype. Make recommendations for enhancements for next studies and

extensive application of the concept. This process guarantees a methodical approach to creating a strong prediction model for a sustainable hybrid energy system based on machine learning, shown in Figure 3.

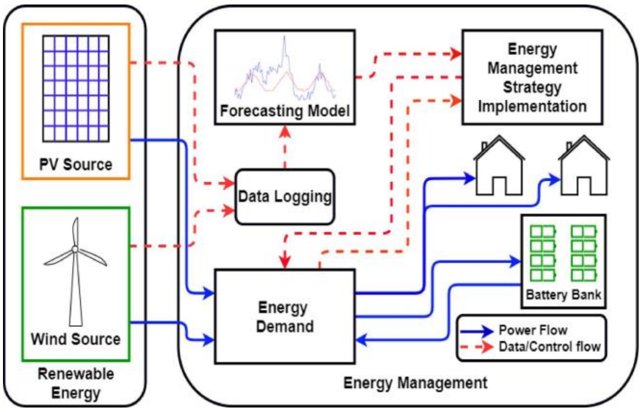


Figure 3 Methodology

4. Hardware Requirements

- Solar Panel Solar panels are composed of photovoltaic (PV) cells that absorb sunlight and convert it into direct current (DC) electricity. They are typically made of silicon and are mounted in an array to form solar modules. The amount of power they produce depends on their efficiency, surface area, and sunlight exposure. In this project, solar panels serve as a clean and renewable energy source that works best during daytime and in sunny weather conditions.
- Wind Turbine (Mini Windmill) A wind turbine captures the kinetic energy of wind using blades that spin a rotor connected to an electrical generator. This mechanical-to-electrical conversion produces DC or AC electricity depending on the system setup. Small-scale wind turbines (2.5–3 kW) are ideal for local or residen- tial use. They are especially useful in hybrid systems to generate power when sunlight is not available, such as during nighttime or cloudy days.
- Battery (Energy Storage System) The battery stores excess energy generated by the solar panels and wind turbine for use during periods of low or no generation (e.g., at night or during calm, cloudy weather). Lithium- ion batteries are often preferred for their higher energy density, longer life, and efficiency. Lead-acid batteries are a cheaper alternative but are bulkier and require maintenance. Batteries ensure a continuous and reliable power supply in the system.
- DC to DC Boost Converter A boost converter is a type of step-up DC-DC converter that increases the voltage from a lower level to a higher level. For example, it can raise the solar panel's output voltage to match the battery charging requirements or the input of an inverter. It helps regulate and stabilize power from fluctuating sources, improving overall system efficiency and reliability.
- Inverter (DC to AC Converter) An inverter is an essential component that converts the DC electricity from the battery or solar panels into AC electricity, which is the standard for most household and industrial appliances. MPPT (Maximum Power Point Tracking) inverters are commonly used in solar systems to extract the maximum power from solar panels by adjusting the operating point based on sunlight conditions.
- Charge Controller The charge controller manages the flow of electricity from the solar and wind sources into the battery. It ensures the battery is charged safely, avoiding overcharging (which damages battery life) and overdischarging (which can cause power loss). Advanced charge controllers come with features like temperature compensation, battery health monitoring, and load con- trol.
- Indicators / Display Unit Indicators provide visual feedback about system performance, such as power generation levels, battery status, or fault warnings. These can be simple LED lights or LCD/LED digital

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displays. Having a display module allows users to monitor energy production, consumption, and efficiency in real-time, which is crucial for system optimization and maintenance.

- Mounting Structure, the mounting structure holds the solar panels and wind turbines in place. For solar panels, the structure is usually tilted at an angle based on the geographic location to maximize sunlight capture. For wind turbines, a tall tower or pole is used to access higher wind speeds. These structures must be durable, corrosion-resistant, and designed to withstand environ- mental conditions such as wind, rain, and temperature changes, shown in Figure 4.

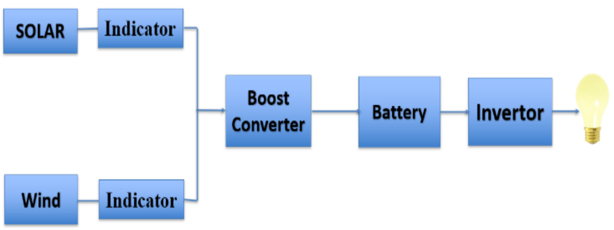

Figure 4 Hardware Setup

- Wiring Electrical Components. This includes cables, connectors, fuses, junction boxes, and protective devices necessary to safely and efficiently connect all system components. Proper wiring ensures minimal energy loss and safe power distribution. Safety components like fuses and surge protectors prevent damage from voltage spikes or system faults.

Conclusions

The Random Forest model outperformed Linear Regression in terms of prediction accuracy, exhibiting a higher R^2 score and lower Root Mean Square Error (RMSE). This indicates that ensemble-based models are better suited for handling the nonlinear and fluctuating nature of renewable energy datasets. The model effectively captured variations in solar irradiance and wind speed, which are crucial for predicting power generation in hybrid systems. In the hardware simulation, real-time weather data in- puts were tested, and the system demonstrated intelligent switching between solar and wind energy sources based on resource availability. When solar irradiance dropped during cloudy conditions, the system automatically shifted to wind energy, ensuring continuous power output with- out manual intervention. This behavior validated the ac- curacy and adaptability of the prediction model in real- world scenarios. Additionally, power generated from both sources was tracked and displayed on an LCD interface, offering user-friendly monitoring. The battery storage system worked efficiently, charging during peak production and supplying power when either source was insufficient. A cost-benefit analysis was also conducted. It showed that while the initial setup cost of the hybrid system is relatively high, the long-term operational savings are substantial—especially in areas with government incentives for renewable energy adoption. Over a period of 5–7 years, the system becomes cost-effective compared to traditional energy sources. Furthermore, the system contributes to reduced carbon emissions and energy in- dependence, making it a sustainable and eco-friendly solution.

Results

"Performance Metrics of Machine Learning Models for Energy Forecasting”. The project “Predictive Modelling with Machine Learning for Sustainable Hybrid Energy System” successfully addresses the critical need for optimizing renew- able energy systems to meet location-specific demands and preferences. By integrating customer input, environ- mental data, and advanced machine learning models, the project demonstrates a systematic approach to designing and recommending cost-effective energy solutions. The predictive model developed in this project provides accurate forecasts of energy outputs for solar, wind, and hybrid systems, validated against publicly available datasets, shown in Table 1.

Table 1 Result

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Model	MAE	RMSE	R^2
Linear Regression	12.3	15.7	0.82
Random Forest	8.7	11.2	0.91
XGBoost	7.5	9.8	0.93
ANN	7.8	10.1	0.92

This enhances the credibility of the model and ensures its practical applicability. Cost analysis further ensures that the recommended solutions are not only energy-efficient but also economically viable for both residential and industrial users. Key findings reveal that hybrid systems often outperform standalone systems in regions with variable wind and solar conditions, while single-resource systems are more suitable for areas with dominant wind or solar availability. These insights can drive informed decision- making for customers, policymakers, and energy stake-holders. Despite its success, the project acknowledges certain limitations, such as the dependency on historical data and the exclusion of real-time weather variations. Future work could focus on incorporating dynamic data streams, exploring advanced predictive algorithms, and expanding the scope to include emerging renewable energy technologies like geothermal or tidal energy. In conclusion, the project not only provides actionable recommendations for sustainable energy planning but also establishes a framework for further advancements in renewable energy system optimization. This contributes significantly to the global transition toward clean and sustainable energy solutions.

Future Scope

The project presents a strong foundation for intelligent hybrid energy systems, and there are several avenues for future enhancement. One major opportunity lies in data enhancement—by integrating real-time data from IoT sensors placed on solar panels, wind turbines, and environmental monitoring stations, the prediction accuracy of energy output can be significantly improved. These sensors can continuously feed updated information on temperature, humidity, solar irradiance, wind speed, and other variables, allowing the system to adapt dynamically to changing conditions. Another promising direction is geographic expansion. While the current model may be tailored to a specific region, it can be generalized and optimized for different climatic zones across the country or even globally. This would involve retraining the models with localized weather and environmental datasets, making the solution scalable and applicable in areas with varying resource availability and environmental patterns.
Finally, technological improvements in machine learning can further boost system performance. Emerging architectures such as Transformer-based models, which have shown remarkable success in various AI domains, can be explored for time-series prediction tasks related to energy generation. These models can handle complex dependencies in data and learn patterns that traditional models might miss, leading to better forecasting and smarter energy system planning.

References

[1]. Ramesh, K., Kumar, P. (2018). "A Comprehensive Review of Solar and Wind Hybrid Systems for Sustainable Energy Development." Renewable Energy.
[2]. Gupta, A., Sharma, N. (2020). "Machine Learning Applications in Renewable Energy Forecasting." Energy Systems.
[3]. Singh, S., Verma, D. (2019). "Cost Optimization of Hybrid Renewable Energy Systems: A Case Study in India." Journal of Renewable Energy Research.
[4]. Ahmed, M., Lee, K. (2021). "Data-Driven Energy anagement Solutions for Hybrid Systems." IEEE Transactions on Smart Grid.
[5]. Chopra, R., Patel, A. (2017). "Advancements in Wind Energy Potential Mapping Using Geographic Data." Renewable and Sustainable Energy Reviews.

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https://doi.org/10.47392/IRJAEH.2025.0379

[6]. Patil, R., Desai, S. (2022). "Solar and Wind Energy Integration for Industrial Applications." Energy Policy.
[7]. Brown, T., Miller, S. (2019). "Predictive Analytics for Renewable Energy Systems." Journal of Energy Analytics.
[8]. Kumar, V., Jain, R. (2021). "Public Dataset Validation for Renewable Energy Forecasting Models." Renewable Data Journal.