Leveraging machine learning for sustainable integration of renewable energy generation

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ABSTRACT

Long-term economic benefits and sustainability are provided by the integration of renewable energy sources (RESs) into electrical networks. However, because of their intermittent nature and reliance on environmental factors, RESs pose issues in production and consumption balance. Because renewable energy sources like wind and solar are unpredictable, forecasting their output is essential for planning purposes and maintaining grid stability. This thesis focuses on developing effective instruments and algorithms to improve renewable energy generation estimates and handle abnormalities in consumption. These tools and algorithms include maximum power point tracking and machine learning models like random forest (RF), adaptive boosting (AdaBoost), and extreme gradient boosting (XGBoost). The methods' effectiveness is confirmed by accuracies higher than 80%, which provides speedier and more user-friendly solutions in comparison to the traditional ways. In the end, our effort seeks to offer practical instruments for anticipatory modelling and mitigating intermittentness in renewable energy sources, enabling their assimilation into current power structures to adequately supply energy requirements in a sustainable manner.

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1. INTRODUCTION

The energy sector is at a turning point in its development, with major sustainability and safety issues that call for quick solutions to avoid instability. There is a clear shift away from fossil fuels, as interest in renewable energy sources like geothermal, wind, and solar power grows [1]‒[3]. In order to avoid blackouts and preserve system stability, striking a balance between the supply and demand of energy is crucial. The generation of energy contributes significantly to greenhouse gas emissions, thus finding sustainable solutions is essential to halting climate change. Nonetheless, more precise forecasting and smooth grid integration are required due to the unpredictability of solar and wind energy output [4]‒[6]. Promising paths for accurate energy forecasting and optimization can be found in machine learning. With the goal of maximizing the penetration of renewable energy sources while minimizing costs, this research suggests a hybrid model for a renewable energy system. The plan places a high priority on sustainability and dependability in order to reduce costs and guarantee effective grid integration [7]‒[10].

Integration challenges with renewables: wind and solar energy are examples of renewable energy sources that require skilled grid management because they are naturally unpredictable owing to environmental conditions. A careful planning and efficient generation approach are essential, as the cost of energy storage systems for solar and wind power is high [11]. Renewable energy systems are increasingly utilizing machine learning to overcome these difficulties. With the use of several machine learning techniques, energy demand is predicted and generation is optimized, aiding in the allocation of resources and the design of policies for short- and medium-term use [12]. Environmental factors must be taken into account while projecting the production of renewable energy. Renewable energy installations can be configured and sited optimally with the use of machine learning [13]–[16]. In intelligent grid management, machine learning is also a useful technique for fault detection and regulation. For instance, utilizing the algorithms random forest (RF) and extreme gradient boosting (XGBoost) on Tripura, India data can improve the integration of renewable energy sources in areas with insufficient infrastructure [17]–[20].

Solutions offered for the difficulties of integrated renewable energy: the challenges created by the variability and unpredictability of renewable energy (RE) output have been addressed in a number of ways [21]. Network features and cost-effectiveness of technology should be taken into account while choosing solutions. The most practicable options are determined by factors like grid infrastructure, operational procedures, generation type, and laws. The management of the intermittent nature of renewable energy sources can be facilitated by several techniques such as demand-side flexibility, energy storage, flexible generation, improved forecasting, and operational tactics [22], [23]. Although they are simpler, short-term forecasts whose forecast mistakes might range from 3-6% an hour ahead of time to 6-8% per day are essential for efficient management:

- Operational techniques: faster dispatch techniques and broader balancing authority regions increase efficiency and provide access to a greater range of resources for balancing, which eliminates the need for pricey regulating reserves.
- Reserve management: the unpredictability of wind and solar power is lessened by modified reserve management techniques, such as lowering power ramps and permitting renewables to deliver reserves or supplemental services.
- Geographic dispersion: local changes affect smaller units rather than the overall output power, hence connecting scattered resources over a wider geographic area lessens the impact of RE intermittence.
- Energy storage: rather of depending on expensive storage systems, large-scale "overbuilding" or curtailment can provide energy storage, which is necessary for minimizing generation curtailment, especially with increasing RE penetration.
- Hybrid systems and demand response: to minimize overall power fluctuations, wind-photovoltaic (PV) hybrid systems take advantage of the complimentary nature of solar and wind outputs. Demand response provides savings over sustaining additional renewable power during rare cases of considerable under-or surplus generation by offering flexibility on the demand side to mitigate rapid ramping impacts.

Through the application of machine learning, better forecasting, and operational methods, these difficulties will be addressed in order to increase the integration of renewable energy sources, promote sustainability, and maintain grid stability [24], [25].

2. METHOD

Ensuring transparency and repeatability for colleague researchers, the experimental/method section provides a thorough overview of the research methods done and the methodologies applied. The experiment's setup, data analysis, and decision-making procedures are all explained in great depth below:

2.1. Experimental configuration

The project focuses on applying an integrated systems approach to incorporate distributed generation, energy storage, demand response, and renewable energy sources into the electrical grid. In order to enable seamless integration, this strategy tackles institutional, financial, legal, and technological impediments. Key tools for estimating wind speed and sun radiation, such as pyranometers and anemometers, were used to gather data from renewable sources. The experimental setup processes wind speed, sun elevation, irradiance, and weather conditions using machine learning approaches.

2.2. Experimental configuration

Carefully gathered data was gathered from many sources, including the State Load Despatch Centre (SLDC), Tripura, and the Ninja Renewables Project. For example, wind power data for the year 2014 in Agartala, Tripura, at an 80-meter height from a Vestas V90 2000 turbine was used. The dataset includes essential factors for wind, solar, and electrical load forecasts and runs from January 2016 to November 2019.

2.3. Experimental configuration

Prediction architecture: IO, NAR, and NARX are three types of autoregressive models: input-output, nonlinear autoregressive, and NAR with exogenous inputs. are the three main designs for time series estimation examined in this paper. Because NARX incorporates historical values in addition to external inputs, it outperforms IO and NAR in situations when exogenous inputs have a major impact on the goal.

2.4. Experimental configuration

The integrated prediction framework used a feature elimination technique to choose input. Iteratively fitting recursive algorithms on smaller feature sets allowed them to optimize for relevance while avoiding the overfitting that is often associated with tree-based models.

2.5. Experimental configuration

RF was used to pick features in order to reduce complexity. XGBoost (XGB), which is well-known for its accuracy in gradient-boosted decision trees, was then applied to training datasets. To improve prediction performance, 10-fold cross-validation was used to optimize hyperparameters such learning rate (eta), maximum depth, and subsample ratio.

2.6. Experimental configuration

Validating and improving predictive models required a thorough investigation of the data. Strictly implemented inclusion/exclusion criteria were based on model performance standards drawn from training and testing datasets as well as statistical significance.

2.7. Experimental configuration

Specifically configured hardware on a Windows GPU platform was used for experiments, which allowed for effective Python execution. An essential component of sustainable power grid management, this configuration guaranteed computational robustness and accuracy in modeling scenarios using renewable energy. Figure 1 shows the overview of power grid with integrated renewable sources and its usage of machine learning techniques.

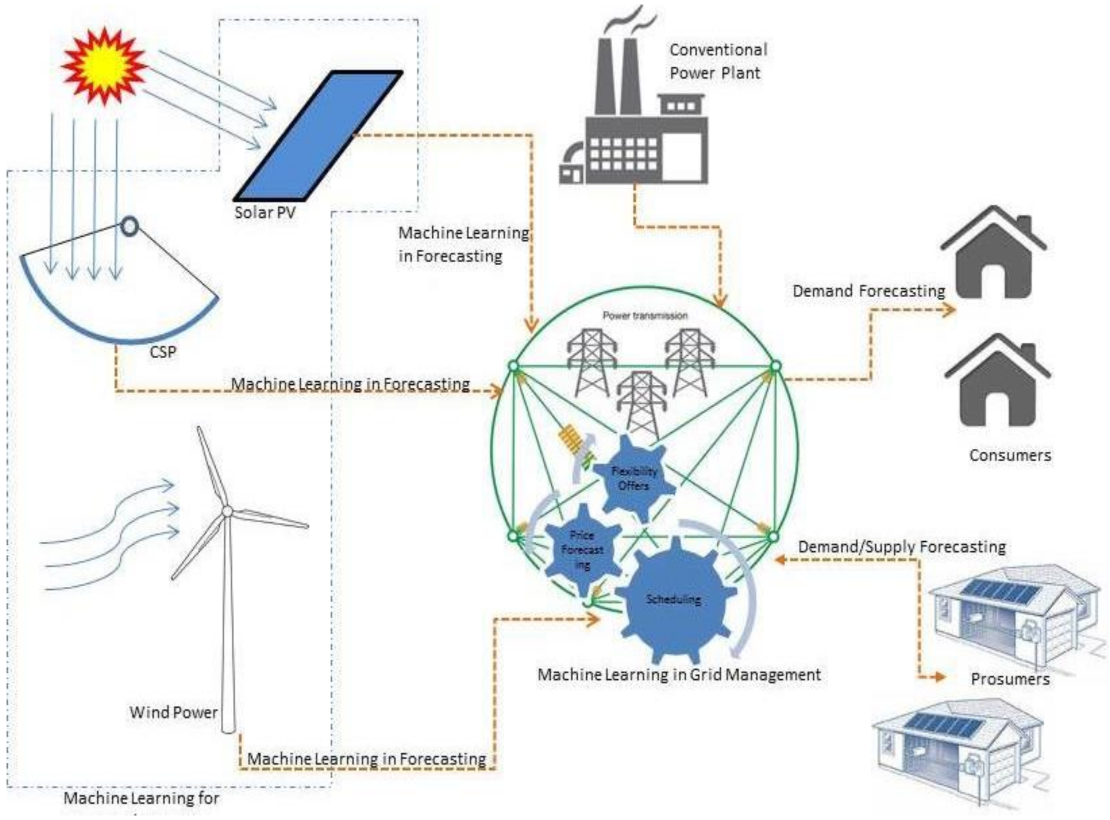


Figure1. Overview of power grid with integrated renewable sources and its usage of machine learning techniques

3. RESULTS AND DISCUSSION

The main study findings are presented in this area, with an emphasis on electrical load projections, wind energy, solar PV power, and model validation. In each paragraph, data attributes are highlighted and prediction algorithms are compared. Table 1 summarizes the inputs for estimates of wind energy, solar PV power, and electrical load.

Table 1. Parameters for forecasting electricity load, solar PV power, and wind energy

Input	Wind energy prediction	Solar PV power prediction	Electricity load prediction
Hourly meteorological parameters	❖	❖	❖
Energy from wind (KW)	❖		
PV solar power (W)		❖	
Power demand (MW)			❖
10 and 50 metre wind speeds	❖	❖	❖
Direction of the wind	❖		
Intensity of sunlight (measured in kilowatts)		❖	❖
Angle of the sun above the horizon		❖	

3.1. Wind energy predictions

The study highlighted the substantial relationship between wind power and wind speed by using RF feature selection to discover significant parameters for wind power prediction. Wind power is also affected by other variables such as humidity, temperature, and time of year. During training, weakly correlated characteristics were removed, and five-fold cross-validation revealed that the predicted wind speed differed very little from the actual data. Figure 2's comparison of the predicted and observed windspeed data illustrates this disparity. Figure 2(a) depicts a forecast for the next day, September 1, 2019; Figure 2(b) depicts a prediction for the next week, September 1, 2019; and Figure 2(c) depicts a long-term forecast for wind speed.

3.2. Solar PV power predictions

The solar PV power and irradiance were projected using a simple algorithm. After generating the target matrix (Y_EPV) using the reliably correlated values from the features matrix (X_EPV), five-fold cross-validation was performed. Figure 3 compares the levels of planned and actual solar PV power and irradiation.

3.3. Electricity load predictions

Data from multiple sources, including Ninja Projects for energy and TSECL, SLDC for load data, were used in the electrical load forecast. Uncertainties and errors were caused by malfunctioning instruments in the load dataset (Agt_load). After the dataset was cleaned up, key characteristics were found. The model was trained using XGBoost, and basic correlation matrices were generated. A combined analysis of predicted electricity load, solar PV power, and wind energy is shown in Table 2. Figure 4 shows the comparison of different models of prediction.

Table 2. An integrated forecasting of wind energy, solar PV power, and electrical load

Model	Wind energy		Solar PV power		Electrical load	
	R^2-score	RMSE	R^2score	RMSE	R^2-score	RMSE
Tree-based decision model	.61	1.35	.79	5.34	.29	4.86
Enhanced decision tree	.65	1.22	.82	5.31	.38	3.24
Support vector regression	.61	2.32	.80	5.71	.59	3.17
Stochastic forest	.66	1.24	.85	5.24	.62	2.82
Enhanced stochastic forest	.78	0.97	.86	5.20	.73	2.69
Ensemble model using XGBoost	.823	0.95	.89	5.02	.76	2.46

3.4. System modelling for reliable integration of renewable sources

To integrate solar and wind energy into Agartala's present power grid, a hybrid system was suggested. The HOMER software was employed to simulate and enhance the system, guaranteeing dependability through modifications to the kinds and quantity of devices. Figure 5 shows the proposed model and the model component specifications are given below, and the optimal configuration minimizes both NPC and LCE.

- PV: 1 KW generic flat plate PV, capital cost: 2,500, replacement: 2,500, O&M: 10/y. Wind: generic 1 KW, capital cost: 7,000, replacement: 7,000, O&M: 70/y.
- Battery: 6 V lithium ion with 1 kWh of energy storage, nominal capacity 167 Ah, max charge current 167a, max discharge current 500a, capital cost: 550, replacement: 550, O&M: 10/y.
- Converter: generic 1 KW, capital: 300, replacement: 300, O&M: 0.0
- Generator: it automatically sizes itself to meet the load. initial capital: 500, replacement: 500, O&M: 0.05 /op. hour, fuel price: 80, emissions: CO(g/L fuel): 16.5, unburned HC: 0.72, fuel sulfur: 2.2, NOx: 15.5.

Configurations with 1,471 KW PV, 315 wind, and 6,999 batteries are economical when compared to LCE and NPC as economic benchmarks; dependability is guaranteed by 1DG, 2,793 KW PV, 222 wind, and 5,246 batteries. These arrangements and the distribution of their electrical load are the subject of more investigation. The comparative examination of the penetration of renewables is shown in Figure 6. Figures 6(a) and 6(b) depict the cost of energy and overall operating costs, respectively, with the highest possible penetration of renewable energy sources.

Figures 6(a) and 6(b) presents an examination of the greatest penetration of renewables with energy and total costs. According to the simulation results, unless battery capacity is large, more than 31% of PV and wind energy output must remain unused for the full renewable contribution (RC=1). As RC falls, waste falls. Important situations consist of: i) low energy excess causes the load to not be satisfied; ii) despite surplus, a third energy source (DG) is required to satisfy 85–100% of the load; and iii) technical load supply could not be energetically satisfying.

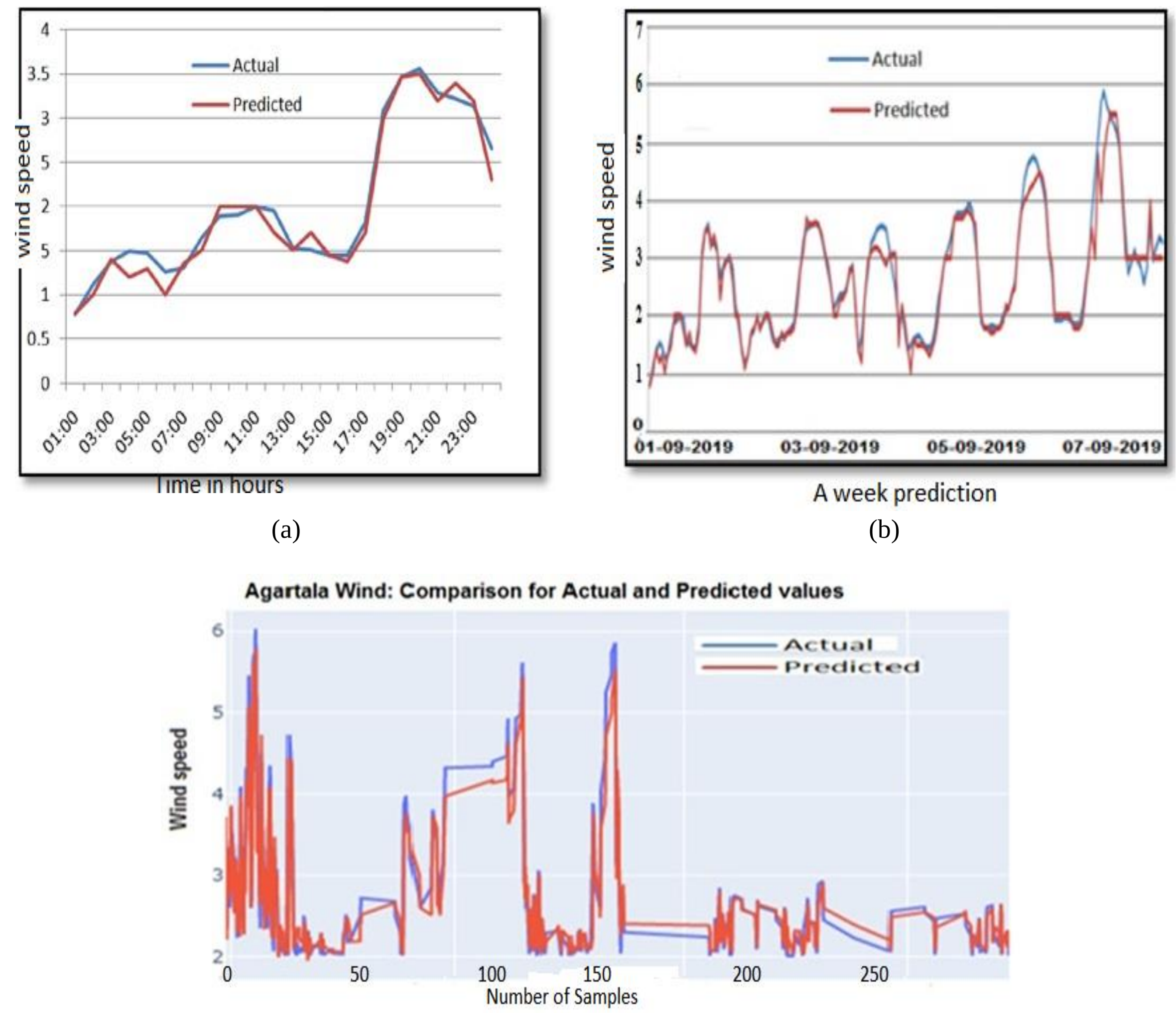


Figure 2. Comparison between forecasted wind speed and observed values: (a) 1-day ahead prediction on 01/09/2019, (b) 1-week ahead prediction (from 01- 07 Sept. 2019), and (c) long term prediction of wind speed

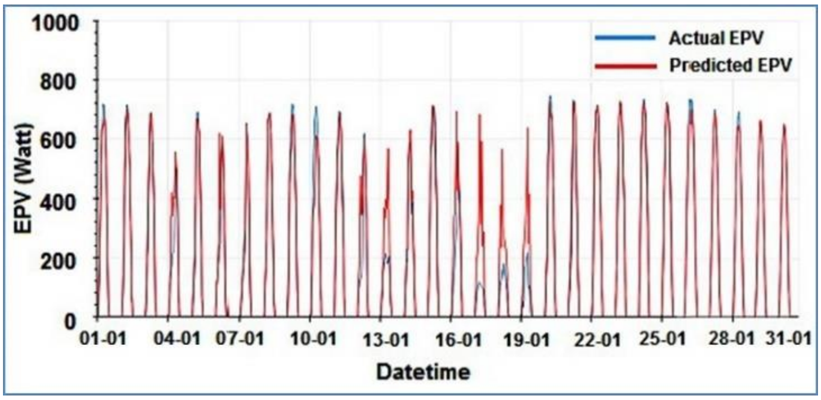


Figure 3. The comparison of actual and predicted values of solar PV power

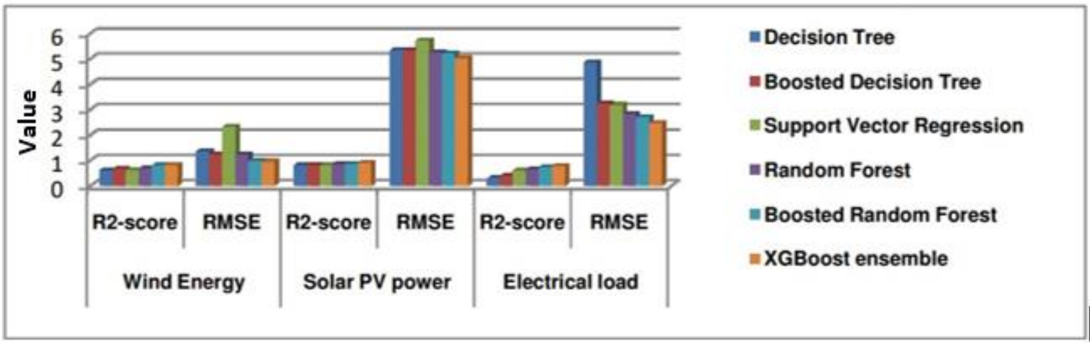


Figure 4. Comparison of different models of prediction

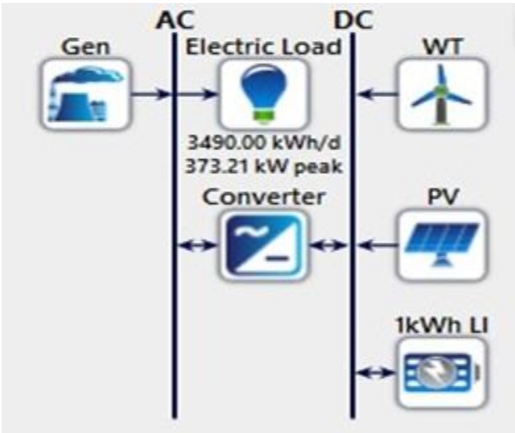
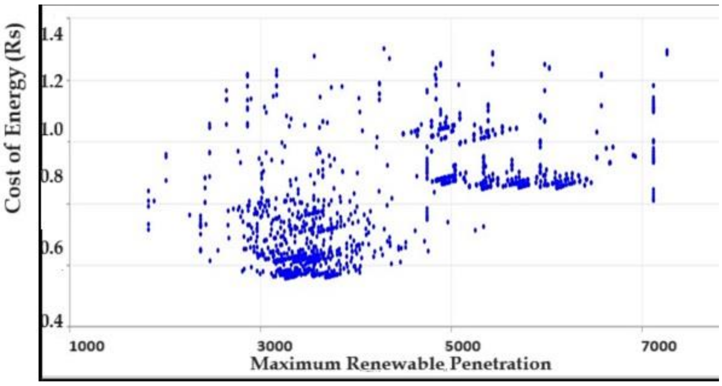


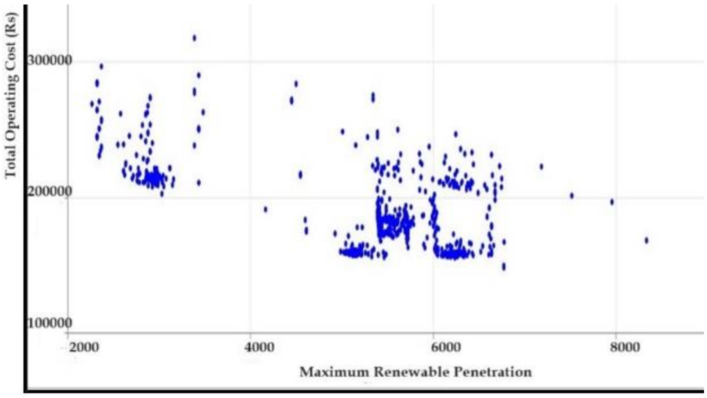
Figure 5. Proposed model

3.5. Interpretation of the results

Improved prediction accuracy for wind energy, solar PV power, and electrical demands, as well as improved integration of renewable energy sources, which are among the goals of the study, which the results support. Similar to previous research, the results demonstrate how well ensemble models like as XGBoost perform in obtaining low root mean square error (RMSE) values and high R2-scores. Some drawbacks include those correct data inputs are necessary for trustworthy forecasts, and a large battery capacity is required to prevent energy waste. For the incorporation of green energy in Agartala, the recommended hybrid setup provides an affordable and dependable option. Optimal performance is achieved with particular combinations.



(a)



(b)

Figure 6. Comparative analysis of renewable penetration with (a) cost of energy and (b) total cost

4. CONCLUSION

As traditional energy sources disappear, renewable energy is becoming more and more popular. Accurate management techniques and forecasting are crucial for a successful integration into power systems, even in the face of uncertainty. Regarding solar, wind, and other replenishable energy sources, metrics such as R2 and RMSE are essential for evaluating predictive analytics. Energy-efficient and cost-effective hybrid storage-based PV and wind systems, optimized with models. By defining the needs for power supply probability method, and system dependability directs decision-making. Effective use of renewable energy depends on battery capacity, and optimizing the use of excess energy can be achieved by integrating diesel as a backup supply and lowering epenses. Data-driven modeling helps with the smooth integration of renewable energy sources into the grid and enhances investment decisions for power storage. Key findings emphasize the need for better predictive models and optimization techniques for smart grid management. Enhanced models like XGBoost show superior predictive accuracy. Investments in power storage technologies are essential to mitigate energy wastage and improve grid reliability. Approaches like LPSP and data-driven models provide strategic insights for balancing cost, reliability, and sustainability.The research advocates for advanced predictive and optimization models to support smart grid enhancements and informed policy and investment decisions. Future research should focus on refining these models to enhance the accuracy and efficiency of renewable energy predictions, crucial for achieving sustainable and resilient energy systems.

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