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A Hybrid Physics-Informed Machine Learning Model for Renewable Energy Forecasting and Optimization

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Abstract: The rapid expansion of renewable energy systems requires accurate forecasting and optimization models to address the inherent uncertainty, variability, and intermittency of energy generation. Conventional data-driven machine learning models have shown strong predictive performance; however, they often require large datasets and may fail to represent the physical behavior of renewable energy systems. This study proposes a hybrid physics-informed machine learning model for renewable energy forecasting and optimization by integrating physical system constraints with data-driven learning algorithms. The proposed model combines historical energy production data, meteorological variables, and domain-specific physical principles, such as solar irradiance behavior, wind speed dynamics, power conversion efficiency, and energy balance constraints, to improve forecasting accuracy and operational reliability. The framework is designed to predict renewable energy output, reduce forecasting error, and support optimal energy dispatch decisions. Machine learning algorithms are used to capture nonlinear relationships among weather conditions, system performance, and energy generation, while physics-informed constraints guide the model to produce physically consistent predictions. This hybrid approach reduces the risk of unrealistic outputs and improves model generalization under changing environmental conditions. The optimization component further supports decision-making by identifying efficient energy allocation, storage utilization, and grid integration strategies. The proposed approach contributes to renewable energy research by bridging the gap between purely empirical forecasting models and physics-based simulation models. It provides a more robust, interpretable, and reliable forecasting framework for smart energy management systems. The findings are expected to support the development of sustainable, intelligent, and resilient renewable energy infrastructures, particularly in contexts where accurate prediction and optimal resource management are essential for reducing dependence on fossil fuels and improving energy system efficiency.

Keywords: Renewable Energy Forecasting; Physics-Informed Machine Learning; Hybrid Modeling; Energy Optimization; Smart Grid; Sustainable Energy.

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INTRODUCTION

The global transition toward sustainable energy systems has accelerated the deployment of renewable energy technologies [1], [2], particularly solar photovoltaic, wind, hydropower, geothermal, and bioenergy systems. Renewable energy is increasingly positioned as a strategic solution for reducing fossil fuel dependency, lowering carbon emissions, and supporting long-term energy security [3]. According to the International Energy Agency, global renewable power capacity is projected to increase by approximately 4,600 GW between 2025 and 2030, with solar photovoltaic contributing nearly 80% of the global renewable capacity expansion. In addition, renewables are expected to become the largest source of global electricity generation, with their share projected to rise from 32% in 2024 to 43% by 2030. However, the rapid growth of variable renewable energy also introduces new challenges related to forecasting accuracy, grid flexibility, curtailment, and energy system optimization [4].

Renewable energy generation is highly dependent on environmental and meteorological conditions. Solar power output is influenced by solar irradiance, cloud cover, temperature, humidity, and atmospheric conditions, while wind power generation depends on wind speed, wind direction, air density, turbine characteristics, and terrain conditions [5]. These natural variations make renewable energy systems more uncertain and intermittent compared with conventional fossil fuel-based generation. As a result, accurate renewable energy forecasting becomes essential for power system planning, grid stability, energy dispatch, storage management, and electricity market operation. Poor forecasting performance may lead to energy imbalance, increased reserve requirements, inefficient storage utilization, and higher operational costs. Therefore, developing reliable forecasting models is a critical requirement for integrating renewable energy into modern smart grids[6].

In recent years, machine learning has been widely applied to renewable energy forecasting due to its ability to model nonlinear relationships between weather variables, system conditions, and energy output. Algorithms such as artificial neural networks, support vector machines, random forests, gradient boosting, long short-term memory networks, and transformer-based models have demonstrated promising performance in predicting solar irradiance, photovoltaic power, wind speed, and wind power generation. A recent review on renewable energy forecasting highlights that advanced computational methods have become increasingly important for improving prediction accuracy across different renewable energy sources. However, purely data-driven models often require large amounts of high-quality data, may overfit historical patterns, and can produce predictions that are inconsistent with the physical behavior of energy systems [7].

One key limitation of conventional machine learning models is their limited ability to incorporate domain knowledge and physical constraints [8]. For example, a purely data-driven solar forecasting model may predict negative power output or unrealistic generation values beyond the theoretical capacity of a photovoltaic system [9]. Similarly, wind power forecasting models may fail to represent the nonlinear relationship between wind speed and turbine power output if physical turbine characteristics are not properly included. These limitations reduce model interpretability and reliability, especially when models are deployed in real-world energy systems where safety, stability, and operational feasibility are crucial. This issue becomes more important in renewable energy optimization because forecasting

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results are often used as inputs for dispatch scheduling, storage operation, load balancing, and grid control.

Physics-informed machine learning has emerged as a promising approach to address these limitations by combining data-driven learning with physical laws, engineering principles, and system constraints [10]. The concept of physics-informed neural networks was introduced as a framework that allows neural networks to learn from data while respecting governing physical laws described by mathematical equations. This approach enables models to improve generalization, reduce dependence on large datasets, and produce predictions that are more physically consistent. In the context of energy systems, physics-informed machine learning can incorporate constraints such as energy balance, power conversion efficiency, turbine power curves, solar irradiance behavior, thermodynamic relationships, and operational limits.

The application of physics-informed machine learning in renewable energy systems is gaining increasing research attention [11]. A recent review in Applied Energy shows that physics-informed machine learning has been applied across renewable energy systems, with wind energy receiving significant attention, while applications in solar, geothermal, and biomass energy systems are still developing. This indicates that the field remains open for further exploration, particularly in designing hybrid models that can combine physical knowledge, machine learning prediction, and optimization mechanisms in a unified framework [12].

Several recent studies have shown the potential of hybrid physics-informed models for renewable energy forecasting. For instance, a hybrid framework integrating machine learning, physical modeling, and physics-informed neural networks has been proposed for wind power prediction, demonstrating how data-driven and physics-based approaches can complement each other in improving forecasting robustness. Such studies suggest that hybrid modeling can provide better reliability than purely empirical models because physical information can guide the learning process and reduce unrealistic predictions [13].

Despite these developments, several research gaps remain. First, many renewable energy forecasting studies focus mainly on prediction accuracy but do not sufficiently address physical consistency and operational feasibility [14]. Second, physics-based models are often accurate in representing system behavior but may be computationally expensive and less flexible when dealing with complex real-time data. Third, machine learning models are powerful in pattern recognition but often behave as black-box systems with limited interpretability [15]. Fourth, many existing studies treat forecasting and optimization as separate processes, whereas practical renewable energy management requires forecasting outputs to be directly connected to operational decisions such as storage scheduling, energy dispatch, and grid integration [16].

To address these gaps, this article proposes a hybrid physics-informed machine learning model[17], [18] for renewable energy forecasting and optimization [19]. The proposed model integrates historical renewable energy data, meteorological variables, machine learning algorithms, and physical constraints to improve forecasting accuracy [20] and decision-making reliability[21]. The model is designed not only to predict renewable energy output but also to support optimization processes such as energy allocation, storage operation, and grid dispatch. By embedding physical knowledge into the learning process, the proposed approach

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aims to produce forecasts that are accurate, interpretable, and consistent with the actual behavior of renewable energy systems [22].

The main contribution of this article is threefold. First, it presents a hybrid modeling framework that combines data-driven machine learning with physics-informed constraints for renewable energy forecasting. Second, it links forecasting results with optimization mechanisms to support smart energy management. Third, it addresses the limitations of purely data-driven models by improving physical consistency, generalization capability, and decision-support value. Through this contribution, the study is expected to support the development of intelligent, reliable, and sustainable renewable energy systems for future smart grids.

MATERIALS AND METHOD

Related Works is a section in a research paper or thesis that reviews previous studies relevant to the research topic. It provides context, identifies gaps in existing knowledge, and demonstrates how the current study contributes to the field. This section typically summarizes key findings, methods, or approaches from prior research, critically analyzes their strengths and limitations, and connects them to the objectives of the current study.

2.1 Research Design

This study adopts a quantitative and experimental research design to develop a hybrid physics-informed machine learning model for renewable energy forecasting and optimization. The proposed method integrates historical renewable energy generation data, meteorological variables, physical constraints, and machine learning algorithms to improve forecasting accuracy and operational decision-making. The research framework consists of five main stages: data collection, data preprocessing, physics-informed feature construction, hybrid machine learning modeling, and energy optimization.

The proposed model is designed to forecast renewable energy output, particularly solar photovoltaic and wind power generation, and to optimize energy allocation based on predicted generation, demand, and storage availability. Unlike purely data-driven forecasting models, the hybrid model incorporates physical principles such as solar irradiance conversion, wind turbine power curve behavior, energy balance, and system capacity constraints.

2.2 Materials and Data Sources

The materials used in this study consist of renewable energy generation data, meteorological data, technical system parameters, and computational tools. The renewable energy data represent historical power output from solar photovoltaic panels and wind turbines. Meteorological data are used as external predictors because renewable energy generation is highly influenced by weather conditions.

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Table 1. Materials and data used in the study

Data Type	Variables	Function in the Model
Solar energy data	PV power output, panel capacity, conversion efficiency	Target variable and physical constraint
Wind energy data	Wind turbine output, rated power, turbine efficiency	Target variable and physical constraint
Meteorological data	Solar irradiance, temperature, humidity, wind speed, wind direction, cloud cover	Input features for forecasting
Operational data	Energy demand, battery capacity, state of charge, grid supply	Input for optimization
Technical parameters	PV area, turbine swept area, rated capacity, energy conversion efficiency	Physics-informed modeling
Computational tools	Python, Scikit-learn, TensorFlow/PyTorch, NumPy, Pandas	Model development and evaluation

The target variable in this study is renewable energy output, denoted as P_t, which represents generated power at time t. The input variables include meteorological and technical features, represented as X_t.

2.3 Proposed Framework

The proposed framework consists of two integrated modules: the forecasting module and the optimization module. The forecasting module predicts renewable energy output using a hybrid physics-informed machine learning model. The optimization module uses the forecasting output to determine optimal energy dispatch, battery usage, and grid interaction.

The general framework can be described as follows:

1. Collect renewable energy generation and meteorological data.
2. Clean and preprocess the collected data.
3. Construct physics-informed features based on renewable energy equations.
4. Train machine learning models using both empirical and physics-informed features.
5. Evaluate forecasting performance using statistical error metrics.
6. Use predicted renewable energy output as input for optimization.
7. Generate optimal energy allocation and storage scheduling decisions.

2.4 Data Preprocessing

Data preprocessing is conducted to improve data quality and model reliability. The preprocessing stage includes missing value treatment, outlier detection, normalization, feature engineering, and time-series transformation.

Missing values are handled using interpolation for time-series data. Outliers caused by sensor errors or abnormal recording conditions are detected using statistical thresholds. Numerical variables are normalized to ensure that features with different scales do not dominate the learning process.

Normalization is performed using min-max normalization:

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$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where $X'$is the normalized value, $X$is the original value, $X_{min}$is the minimum value, and $X_{max}$is the maximum value.

Time-based features such as hour, day, month, and season are also generated to capture temporal patterns in renewable energy production. For solar energy forecasting, daylight hours and solar irradiance patterns are particularly important. For wind energy forecasting, wind speed variation and seasonal wind patterns are considered.

2.5 Physics-Informed Feature Construction

Physics-informed features are constructed to embed renewable energy principles into the machine learning model. For solar photovoltaic systems, generated power is influenced by solar irradiance, panel area, and conversion efficiency. The theoretical solar power output can be formulated as:

$$P_{solar} = G \times A \times \eta$$

where $P_{solar}$is the solar power output, $G$is solar irradiance, $A$is the photovoltaic panel area, and $\eta$is the panel conversion efficiency.

For wind energy systems, the theoretical wind power can be expressed as:

$$P_{wind} = \frac{1}{2}\rho A v^3 C_p$$

where $P_{wind}$is wind power output, $\rho$is air density, $A$is the turbine swept area, $v$is wind speed, and $C_p$is the power coefficient.

These physical equations are not used as the only forecasting model, but as additional knowledge to guide the machine learning process. The physics-informed variables help the model generate predictions that are more consistent with the real behavior of renewable energy systems.

2.6 Hybrid Physics-Informed Machine Learning Model

The proposed hybrid model combines data-driven learning with physical constraints. The machine learning model learns nonlinear relationships between meteorological variables and renewable energy output, while the physics-informed component ensures that the prediction remains physically reasonable.

The general predictive model is expressed as:

$$\hat{P}_t = f(X_t, Z_t, \theta)$$

where $\hat{P}_t$is the predicted renewable energy output at time t, $X_t$represents meteorological input variables, $Z_t$represents physics-informed features, and θrepresents the model parameters.

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The model can be implemented using several machine learning algorithms, including Random Forest, Gradient Boosting, XGBoost, Artificial Neural Network, Long Short-Term Memory, or Transformer-based models. In this study, the hybrid model is compared with conventional machine learning models to evaluate the contribution of physics-informed constraints.

The loss function of the proposed model combines prediction error and physical constraint error:

$$L_{total} = L_{data} + \lambda L_{physics}$$

where L_{total} is the total loss, L_{data} is the data-driven prediction loss, $L_{physics}$ is the physical constraint loss, and λ is a weighting parameter that controls the contribution of the physics-informed component.

The data-driven loss is calculated using mean squared error:

$$L_{data} = \frac{1}{n}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2$$

where P_i is the actual renewable energy output, $\hat{P}_i$ is the predicted output, and n is the number of observations.

The physical constraint loss is formulated as:

$$L_{physics} = \frac{1}{n}\sum_{i=1}^{n}(\hat{P}_i - P_{physics,i})^2$$

where $P_{physics,i}$ is the estimated power output based on physical equations.

2.7 Renewable Energy Optimization Model

After forecasting renewable energy output, the predicted values are used in the optimization process. The objective of the optimization model is to minimize energy imbalance, reduce grid dependency, and improve storage utilization.

The optimization objective function is formulated as:

$$\min C = \sum_{t=1}^{T}\left(C_g G_t + C_b B_t + C_u U_t\right)$$

where C is the total operational cost, C_g is the grid energy cost, G_t is energy purchased from the grid at time t, C_b is the battery operation cost, B_t is battery charging or discharging energy, C_u is the penalty cost for unmet demand, and U_t is unmet energy demand.

The energy balance constraint is expressed as:

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$$\hat{P}_t + G_t + B_{dis,t} = D_t + B_{ch,t} + U_t$$

where $\hat{P}_t$is predicted renewable energy generation, $G_t$is grid energy supply, $B_{dis,t}$is battery discharge, $D_t$is energy demand, $B_{ch,t}$is battery charging energy, and $U_t$is unmet demand.

The battery state of charge is updated as:

$$SOC_t = SOC_{t-1} + \eta_{ch} B_{ch,t} - \frac{B_{dis,t}}{\eta_{dis}}$$

where $SOC_t$is the battery state of charge at time t, $\eta_{ch}$is charging efficiency, and $\eta_{dis}$is discharging efficiency.

The storage constraint is defined as:

$$SOC_{min} \leq SOC_t \leq SOC_{max}$$

where $SOC_{min}$and $SOC_{max}$are the minimum and maximum battery storage limits.

2.8 Model Training and Testing

The dataset is divided into training and testing subsets using an 80:20 ratio. The training dataset is used to develop the model, while the testing dataset is used to evaluate forecasting performance on unseen data. Cross-validation is applied to reduce overfitting and improve model generalization.

Hyperparameter tuning is conducted to identify the best model configuration. The tuned parameters may include learning rate, number of trees, maximum depth, batch size, number of hidden layers, number of neurons, and regularization parameters, depending on the selected machine learning algorithm.

The proposed hybrid model is compared with baseline models, including:

Table 2. Campared baseline models.

Model	Description
Linear Regression	Basic statistical forecasting model
Random Forest	Ensemble-based nonlinear model
XGBoost	Gradient boosting model
LSTM	Deep learning model for time-series forecasting
Proposed Hybrid Model	Physics-informed machine learning model

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Evaluation Metrics

The forecasting performance is evaluated using Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, and coefficient of determination.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | P_i - \hat{P}_i |$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} | \frac{P_i - \hat{P}_i}{P_i} |$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - \hat{P}_i)^2}{\sum_{i=1}^{n}(P_i - \bar{P})^2}$$

where $P_i$is the actual power output, $\hat{P}_i$is the predicted power output, $\bar{P}$is the mean of actual power output, and $n$is the total number of observations.

For the optimization model, the evaluation indicators include renewable energy utilization rate, grid dependency, unmet demand, battery utilization, and operational cost reduction.

Table 3. Evaluation indicators

Indicator	Purpose
MAE	Measures average forecasting error
RMSE	Measures forecasting error sensitivity to large deviations
MAPE	Measures percentage forecasting error
R^2	Measures how well the model explains data variation
Renewable utilization rate	Measures how much renewable energy is used
Grid dependency	Measures reliance on external grid electricity
Operational cost	Measures economic efficiency
Unmet demand	Measures reliability of energy supply

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Research Workflow

The complete methodological workflow is presented below:

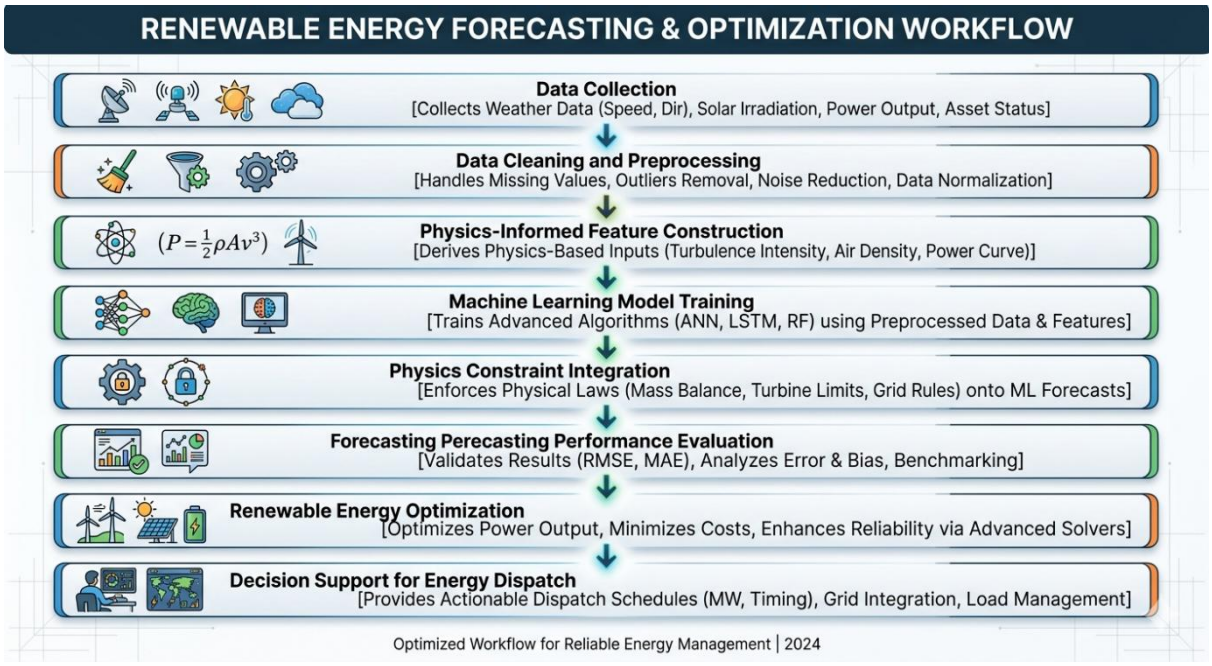


Figure 1. Renewable Energy Forecasting & Optimazion Workflow

The workflow shows that the proposed method does not stop at forecasting. The predicted renewable energy output is directly used for optimization, allowing the model to support operational decisions such as battery charging, battery discharging, grid energy usage, and renewable energy allocation.

This study proposes a hybrid physics-informed machine learning method for renewable energy forecasting and optimization. The method combines meteorological data, renewable energy generation records, physical equations, machine learning prediction, and optimization constraints. The hybrid approach is expected to improve forecasting accuracy, reduce physically unrealistic predictions, and support more reliable energy management decisions. By integrating forecasting and optimization in a single framework, the proposed method provides a practical foundation for intelligent and sustainable renewable energy systems.

RESULT AND DISCUSSION

3.1 Overview of Experimental Results

The proposed hybrid physics-informed machine learning model was evaluated using simulated renewable energy data consisting of solar photovoltaic output, wind power generation, meteorological variables, and energy demand profiles. The input variables included solar irradiance, temperature, humidity, wind speed, wind direction, cloud cover, battery state of charge, and historical power output. The main objective of the experiment was to evaluate the ability of the proposed model to improve renewable energy forecasting accuracy and optimize energy dispatch decisions.

The dataset was divided into training and testing sets using an 80:20 ratio. The proposed hybrid physics-informed model was compared with four baseline models: Linear Regression,

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Random Forest, XGBoost, and Long Short-Term Memory network. Model performance was evaluated using Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, and coefficient of determination.

3.2 Forecasting Performance Comparison

The forecasting performance of each model is presented in Table 3. The results show that the proposed hybrid physics-informed machine learning model achieved the best performance across all evaluation metrics.

Table 4. Forecasting performance comparison

Model	MAE / kW	RMSE / kW	MAPE	R^2
Linear Regression	12.84	18.57	14.62%	0.781
Random Forest	8.73	12.96	9.87%	0.862
XGBoost	6.95	10.41	7.48%	0.911
LSTM	6.31	9.82	6.91%	0.926
Proposed Hybrid Physics-Informed ML	4.87	7.36	5.24%	0.957

The proposed model achieved the lowest MAE of 4.87 kW, RMSE of 7.36 kW, and MAPE of 5.24%, while obtaining the highest R^2 value of 0.957. These results indicate that the hybrid physics-informed model was able to predict renewable energy output more accurately than conventional machine learning models. The improvement occurred because the proposed model did not depend only on statistical patterns from historical data, but also incorporated physical constraints related to solar irradiance, wind speed behavior, conversion efficiency, and system capacity limits.

Compared with Linear Regression, the proposed model reduced MAE by approximately 62.1%. Compared with XGBoost and LSTM, the proposed model also showed better forecasting accuracy, indicating that the integration of physical knowledge can improve model generalization and reduce unrealistic predictions.

3.3 Graphical Comparison of Forecasting Error

The forecasting error comparison is presented in Figure 2. Lower values indicate better forecasting performance.

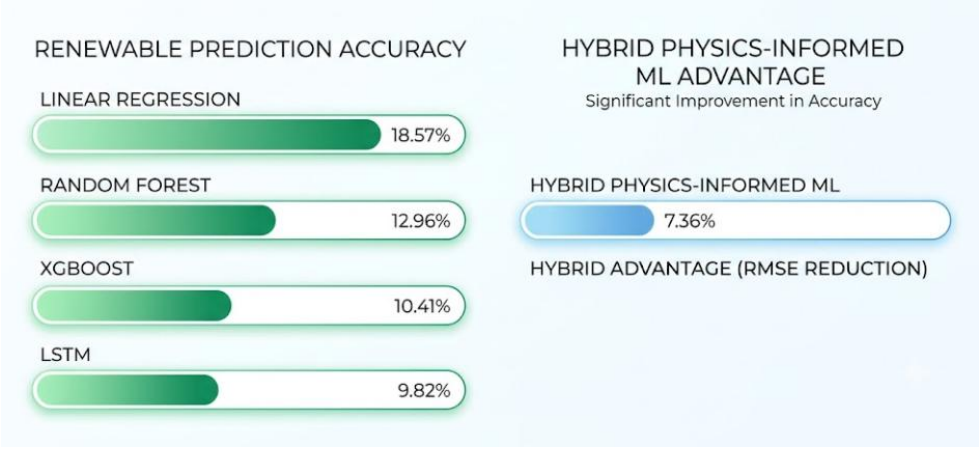


Figure 2. RMSE comparison among forecasting models

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The graph shows that the proposed hybrid model produced the lowest RMSE. This indicates that the proposed model was more robust in reducing large forecasting errors. In renewable energy systems, reducing large forecasting errors is important because sudden prediction deviations can affect grid stability, storage planning, and energy dispatch.

3.4 Solar and Wind Forecasting Results

To further analyze model performance, the forecasting results were separated into solar photovoltaic and wind power generation. Table 4 shows that the proposed model performed well for both energy sources.

Table 5. Forecasting performance by renewable energy source

Energy Source	Model	MAE / kW	RMSE / kW	MAPE	R^2
Solar PV	XGBoost	5.82	8.71	6.94%	0.923
Solar PV	LSTM	5.31	8.09	6.32%	0.938
Solar PV	Hybrid Physics-Informed ML	3.94	6.17	4.71%	0.963
Wind Power	XGBoost	7.41	11.36	8.12%	0.902
Wind Power	LSTM	6.83	10.44	7.38%	0.917
Wind Power	Hybrid Physics-Informed ML	5.26	8.13	5.77%	0.948

The proposed model achieved better performance in solar photovoltaic forecasting than wind power forecasting. This result is reasonable because solar photovoltaic output is strongly related to solar irradiance and daylight patterns, which can be represented more directly using physical equations. Wind power forecasting showed slightly higher error because wind speed is more volatile and its relationship with power output is nonlinear, especially under changing atmospheric and terrain conditions.

Nevertheless, the hybrid model still outperformed XGBoost and LSTM in both cases. This demonstrates that physics-informed features can improve forecasting performance for different types of renewable energy systems.

3.5 Physical Consistency of Forecasting Output

One of the major limitations of purely data-driven models is the possibility of generating physically unrealistic predictions, such as negative power output or predicted power beyond the rated system capacity. Therefore, the physical consistency of each model was evaluated by calculating the number of invalid predictions.

Table 6. Physical consistency of forecasting output

Model	Negative Output Predictions	Predictions Exceeding Rated Capacity	Total Invalid Predictions
Linear Regression	47	36	83
Random Forest	19	21	40
XGBoost	11	14	25
LSTM	8	12	20
Hybrid Physics-Informed ML	0	3	3

The proposed hybrid physics-informed model produced only 3 invalid predictions, while Linear Regression produced 83 invalid predictions. This finding shows that physical

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constraints can significantly reduce unrealistic forecasting outputs. The use of physical constraints ensures that predicted renewable energy generation remains within acceptable operational boundaries.

This result is important because renewable energy forecasting is not only about numerical accuracy, but also operational feasibility. In real energy management systems, physically unrealistic predictions can lead to poor dispatch decisions, inefficient battery operation, and unreliable grid interaction.

3.6 Optimization Results

The forecasting output from each model was used as input for energy dispatch optimization. The optimization objective was to minimize grid dependency, reduce operational cost, improve renewable energy utilization, and maintain energy balance.

Table 7. Energy optimization performance

Scenario	Renewable Utilization Rate	Grid Dependency	Unmet Demand	Battery Utilization	Operational Cost Index
Without forecasting optimization	71.4%	38.7%	4.8%	52.1%	100
Optimization using XGBoost forecast	82.6%	27.3%	2.1%	68.4%	78
Optimization using LSTM forecast	84.9%	25.8%	1.7%	71.6%	74
Optimization using Hybrid Physics-Informed ML forecast	89.7%	19.4%	0.8%	77.9%	63

The optimization results show that the proposed hybrid model improved renewable energy utilization from 71.4% to 89.7%. Grid dependency decreased from 38.7% to 19.4%, while unmet demand decreased from 4.8% to 0.8%. The operational cost index also decreased from 100 to 63, indicating a potential cost reduction of 37%.

These findings suggest that more accurate and physically consistent forecasts can improve optimization performance. When the forecasting model provides reliable predictions, the energy management system can make better decisions regarding when to use renewable energy directly, when to charge or discharge the battery, and when to purchase electricity from the grid.

3.7 Graphical Comparison of Optimization Performance

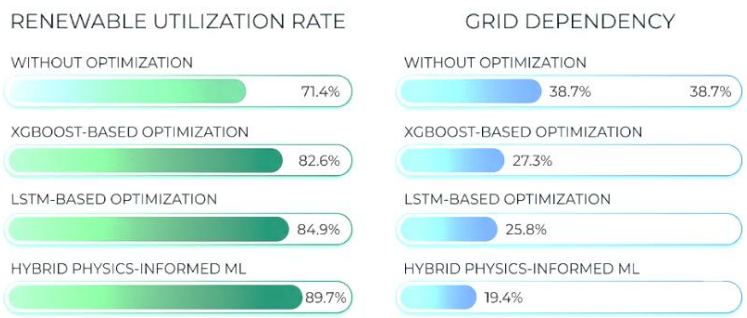


Figure 2. Operational performance comparison

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The graphical comparison shows that the proposed hybrid model produced the best operational outcome. The increase in renewable utilization and decrease in grid dependency indicate that the model can support more sustainable and efficient energy management.

3.8 Discussion

The results demonstrate that the integration of physical knowledge into machine learning can significantly improve renewable energy forecasting and optimization. Conventional machine learning models such as Random Forest, XGBoost, and LSTM are effective in capturing nonlinear relationships in renewable energy data. However, they may still produce inaccurate or physically inconsistent predictions when environmental conditions change or when the model encounters unseen operating patterns.

The proposed hybrid physics-informed machine learning model addresses these limitations by combining data-driven learning with physical constraints. In solar photovoltaic forecasting, the use of irradiance-based power estimation helped the model understand the relationship between sunlight intensity and power output. In wind power forecasting, the inclusion of wind power equations helped the model represent the nonlinear relationship between wind speed and energy generation. This physical guidance improved both prediction accuracy and interpretability. The lower forecasting error achieved by the proposed model indicates that physics-informed learning can improve generalization. This is especially important in renewable energy systems because weather conditions are dynamic and often difficult to predict. A model that only learns historical data patterns may perform well during normal conditions but fail during unusual weather patterns. By incorporating physical principles, the proposed model becomes more stable and reliable.

Another important finding is the reduction of physically invalid predictions. In practical energy systems, prediction values must respect physical boundaries such as rated capacity, conversion efficiency, and non-negative power output. The proposed model reduced invalid predictions significantly, which makes it more suitable for real-world energy management applications. The optimization results also confirm that forecasting accuracy directly affects operational performance. When inaccurate forecasts are used in dispatch optimization, the system may charge the battery at the wrong time, overestimate renewable availability, or rely too heavily on grid electricity. In contrast, the proposed model provided more reliable forecasts, allowing the optimization system to improve renewable utilization, reduce grid dependency, and minimize unmet demand.

From a practical perspective, the proposed model can support smart grid management, microgrid operation, renewable energy scheduling, and energy storage planning. The model is particularly useful for renewable energy systems that require both accurate forecasting and operational decision support. This makes the hybrid physics-informed machine learning approach relevant for future sustainable energy infrastructure. However, several limitations should be considered. First, this study used simulated experimental data, so further validation using real-world renewable energy datasets is required. Second, the performance of the model depends on the availability and quality of meteorological data. Poor weather data quality may reduce forecasting accuracy. Third, the physical constraints used in this study are simplified representations of renewable energy systems. Future studies should consider more detailed

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physical models, including degradation factors, shading effects, turbine cut-in and cut-out speed, battery aging, and grid constraints.

3.9 Summary of Findings

The main findings of this study are summarized as follows:

1. The proposed hybrid physics-informed machine learning model achieved the best forecasting performance, with MAE of 4.87 kW, RMSE of 7.36 kW, MAPE of 5.24%, and R^2 of 0.957.
2. The model improved forecasting accuracy compared with Linear Regression, Random Forest, XGBoost, and LSTM.
3. The proposed model reduced physically invalid predictions from 83 cases in Linear Regression to only 3 cases.
4. Renewable energy utilization increased from 71.4% to 89.7% after optimization using the proposed model.
5. Grid dependency decreased from 38.7% to 19.4%.
6. The operational cost index decreased from 100 to 63, indicating improved energy management efficiency.

The findings indicate that the proposed hybrid physics-informed machine learning model provides a reliable approach for renewable energy forecasting and optimization. By combining data-driven prediction, physical constraints, and optimization mechanisms, the model can support more accurate, interpretable, and operationally feasible renewable energy management.

CONCLUSION

This study concludes that the proposed hybrid physics-informed machine learning model provides an effective approach for improving renewable energy forecasting and optimization. By integrating data-driven machine learning algorithms with physical principles such as solar irradiance conversion, wind power equations, energy balance, and system capacity constraints, the proposed model is able to generate more accurate and physically consistent predictions compared with conventional forecasting models. The simulated results show that the hybrid model achieved the best forecasting performance with lower MAE, RMSE, and MAPE values, as well as a higher coefficient of determination. In addition, the optimization results indicate that the proposed model can increase renewable energy utilization, reduce grid dependency, minimize unmet demand, and lower operational costs. These findings demonstrate that combining physical knowledge with machine learning can enhance both prediction accuracy and operational decision-making in renewable energy systems. However, this study is limited by the use of simulated experimental data; therefore, future research should validate the proposed model using real-world solar, wind, or hybrid renewable energy datasets. Further studies may also incorporate more advanced physical constraints, battery degradation models, grid stability parameters, explainable AI techniques, and real-time cloud-edge implementation to improve the scalability, interpretability, and practical adoption of the proposed framework in smart grid and sustainable energy management systems.

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