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MACHINE LEARNING-BASED RENEWABLE ENERGY FORECASTING AND OPTIMIZATION TECHNIQUES

Sumaira Ameen
BS, Department of English, The Cosmic Degree College (For Women) ,University of Okara

ABSTRACT

The increasing integration of renewable energy sources into modern power systems has created a growing need for accurate forecasting and efficient optimization techniques. Solar and wind energy generation are inherently variable because of changing weather conditions, seasonal patterns, atmospheric disturbances, and geographical characteristics. These uncertainties create challenges for electricity generation planning, energy storage management, grid stability, and power distribution. Machine learning (ML) has emerged as a promising approach for addressing these challenges by identifying complex relationships within historical energy production, meteorological, and electricity demand data. This study examines machine learning-based renewable energy forecasting and optimization techniques, with particular emphasis on artificial neural networks, random forests, support vector regression, long short-term memory networks, and hybrid deep learning models. It also investigates the application of optimization algorithms to improve energy scheduling, storage utilization, resource allocation, and operational efficiency. A quantitative, comparative research framework is proposed using historical renewable energy generation, weather variables, and electricity demand data. Forecasting performance is evaluated using mean absolute error, root mean square error, mean absolute percentage error, and coefficient of determination, while optimization performance is assessed through operational cost, renewable energy utilization, storage efficiency, and forecast-related decision improvements. The study develops an integrated conceptual framework in which predictive models inform optimization decisions under changing environmental and operational conditions. It is expected to demonstrate that appropriately selected machine learning models, combined with robust optimization techniques, can support more reliable renewable energy integration, reduce forecasting errors, and improve resource utilization. The research also highlights the importance of data quality, model interpretability, computational efficiency, and uncertainty management in the practical deployment of intelligent renewable energy systems.

Keywords:*Machine learning, renewable energy forecasting, solar power prediction, wind energy forecasting, deep learning, long short-term memory networks, predictive analytics, energy optimization, smart grids, energy storage management, forecasting accuracy, sustainable energy systems, and power system efficiency.*

INTRODUCTION

Renewable energy has become an essential component of global strategies for reducing greenhouse gas emissions, strengthening energy security, and supporting sustainable economic development. Solar photovoltaic systems, wind turbines, hydropower facilities, and other renewable technologies are increasingly incorporated into electricity generation networks. Barhmi, K., Heynen, C., Golroodbari, S., & van Sark, W. (2024, February). found that Unlike conventional power plants that can often provide relatively controllable output, solar and wind installations depend heavily on environmental conditions. Solar electricity production changes with solar irradiance, cloud cover, temperature, and daylight duration, whereas wind power generation depends on wind speed, wind direction, air density, and turbine characteristics. These variations introduce uncertainty into electricity supply and create challenges for grid operators and energy planners. Consequently, accurate renewable energy forecasting and efficient operational optimization have become important research priorities.Renewable energy forecasting involves estimating future electricity generation, energy demand, or resource availability over different time horizons. Short-term forecasts support real-time grid balancing, intraday electricity trading, and battery scheduling, while medium-term forecasts assist maintenance planning, reserve allocation, and operational

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scheduling. Long-term predictions can contribute to infrastructure planning and investment decisions. Traditional forecasting methods, including statistical regression, autoregressive models, and physical simulation techniques, have provided useful foundations for energy prediction. However, their effectiveness may decline when data contain nonlinear relationships, complex temporal dependencies, abrupt weather changes, and interactions among multiple environmental variables. These limitations have encouraged the development of data-driven forecasting methods that can learn complicated patterns directly from historical observations.

Machine learning provides a collection of computational techniques that learn predictive relationships from historical data without requiring every relationship to be explicitly programmed. Methods such as random forests, gradient boosting, support vector regression, artificial neural networks, and recurrent neural networks can process multiple predictors and capture nonlinear interactions between weather conditions and renewable electricity production. Deep learning approaches, particularly long short-term memory (LSTM) networks and temporal convolutional architectures, can also identify sequential patterns in time-series observations. Their effectiveness depends on appropriate model selection, feature engineering, data volume, and validation procedures. Machine learning therefore offers substantial potential for improving forecasting accuracy, although complex models are not automatically superior to simpler statistical alternatives in every dataset or operating environment.Forecasting alone does not guarantee efficient energy management because predicted generation must be translated into practical operational decisions. Optimization techniques can use forecast outputs to determine when to charge or discharge batteries, how to allocate electricity among consumers, how to schedule flexible loads, and how to coordinate renewable generation with conventional power sources. Benitez, I. B., & Singh, J. G. (2025). Explained that Mathematical programming, stochastic optimization, evolutionary algorithms, particle swarm optimization, and model predictive control are among the approaches used for these purposes. When forecasting and optimization are integrated, the forecasting model estimates future conditions while the optimization component identifies operational decisions that satisfy system constraints and minimize a specified objective, such as cost, emissions, or renewable energy curtailment. This integration is particularly valuable in systems characterized by fluctuating generation and limited storage capacity.

Despite substantial advances in machine learning, several challenges remain in renewable energy forecasting and optimization. Renewable energy datasets frequently contain missing observations, inconsistent sampling intervals, sensor errors, and changes in operating conditions. Models trained on one location or season may perform poorly when transferred to another geographical region or weather regime. Furthermore, improvements in prediction accuracy do not necessarily translate into lower electricity costs or better operational outcomes. Some sophisticated models require substantial computational resources and offer limited interpretability, complicating their adoption by electricity utilities and energy planners. Research is therefore needed to evaluate forecasting models under consistent experimental conditions and to establish how their predictions can be incorporated into optimization procedures that account for uncertainty, technical constraints, and practical performance indicators. Di Leo, P., Ciocia, A., Malgaroli, G., & Spertino, F. (2025). Explains that This study investigates machine learning-based renewable energy forecasting and optimization techniques through an integrated research framework. It focuses on comparing predictive models, identifying relevant meteorological and historical generation features, evaluating forecast accuracy, and examining the influence of prediction quality on energy

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management decisions. The study proposes a reproducible quantitative methodology based on time-ordered data, baseline comparisons, appropriate error metrics, and constrained optimization. Its central contribution is the development of a framework that connects forecasting performance with operational outcomes rather than treating prediction and optimization as separate tasks. The research is intended to provide useful guidance for renewable energy researchers, grid operators, policymakers, and energy system designers seeking to improve the reliability, efficiency, and sustainability of electricity generation and distribution.

RESEARCH QUESTION

1. How can machine learning-based forecasting models integrated with optimization techniques improve renewable energy prediction accuracy, operational efficiency, and renewable energy utilization compared with conventional forecasting and decision-making approaches?

RESEARCH OBJECTIVES

1. To examine the effectiveness of machine learning algorithms in forecasting solar and wind energy generation.

LITERATURE REVIEW

Renewable energy forecasting has developed from conventional statistical approaches toward increasingly sophisticated artificial intelligence and machine learning systems. Earlier forecasting methods commonly relied on regression, time-series analysis, physical weather models, and mathematical relationships between environmental conditions and energy production. Horat, N., Klerings, S., & Lerch, S. (2025). revealed that Although these methods remain useful for particular forecasting horizons, their ability to represent complex nonlinear patterns may be limited when weather conditions change rapidly or when multiple predictors interact. The expansion of renewable energy installations and the increasing availability of high-resolution sensor data have encouraged researchers to investigate data-driven approaches capable of learning directly from observed generation and environmental measurements. Teixeira et al. (2024) reviewed renewable energy forecasting methods and emphasized that forecasting approaches must be selected according to the characteristics of the energy source, the prediction horizon, and the intended application. The evolution of forecasting techniques also reflects a shift from isolated prediction tasks toward integrated energy management. Earlier studies frequently evaluated forecasting systems primarily through prediction errors, whereas contemporary research increasingly considers how forecasts influence grid operations, energy markets, and storage management. Van Poecke et al. (2024) discussed the forecasting process through the distinction between direct and indirect forecasting methods, highlighting the importance of data inputs, time horizons, and the structure of the forecasting pipeline. Direct methods estimate the required energy output from available predictors, while indirect methods may first estimate an intermediate variable, such as solar irradiance or wind speed, before translating it into electricity generation. The selection between these approaches affects the sources of uncertainty and the practical complexity of the forecasting system. Consequently, an effective forecasting framework must

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consider not only the algorithm but also the entire sequence of data collection, prediction, validation, and operational use.

Conventional machine learning methods remain important in renewable energy forecasting because they can offer a useful balance between predictive accuracy, computational efficiency, and implementation complexity. Random forests combine multiple decision trees to generate predictions that are less dependent on an individual tree, while gradient-boosting methods sequentially improve predictive performance by learning from previous errors. Support vector regression identifies predictive relationships through an optimization-based learning procedure, and artificial neural networks represent nonlinear relationships using interconnected computational units. These methods can incorporate meteorological conditions, historical generation, calendar variables, and other relevant predictors. Their performance depends on the quality of the input data, the selected features, hyperparameter configuration, and the forecasting horizon. Liu, Z., Guo, H., Zhang, Y., & Zuo, Z. (2025). Elaborated on A study of photovoltaic generation forecasting published in Energy in 2023 compared several machine learning approaches using real-time data and reported favorable performance from random forest models within its particular experimental setting. This illustrates why conventional algorithms should remain part of comparative evaluations rather than being automatically displaced by more complex architectures. The comparative advantages of conventional machine learning are also relevant to smaller renewable energy installations and distributed energy systems. Such systems may have limited historical data, restricted computing resources, or insufficient technical capacity to maintain complex deep learning models. Tree-based methods can capture nonlinear relationships and interactions without requiring extensive manual specification of functional forms. Support vector regression can perform effectively on structured datasets when its kernel and regularization parameters are appropriately selected.

Deep learning has expanded renewable energy forecasting by enabling models to learn hierarchical representations and complex temporal relationships from large datasets. LSTM networks are designed to retain relevant information across sequential observations, making them suitable candidates for forecasting applications in which recent weather and generation patterns influence future output. Gated recurrent units provide a related architecture with a different gating structure, while convolutional neural networks can identify local patterns in sequential or spatially organized inputs. These architectures can be combined with attention mechanisms and other components to capture relationships across different time intervals. However, deep learning generally requires careful model design, adequate training data, computational resources, and robust validation. Its greater complexity does not guarantee better performance on every renewable energy dataset, especially when the available observations are limited or contain substantial measurement errors.Recent solar forecasting research demonstrates the continuing development of these architectures. Barhmi et al. (2024) reviewed solar forecasting techniques and the role of artificial intelligence across different prediction horizons, showing the importance of matching forecasting techniques to the temporal requirements of the application. Mucomole, F. V., Silva, C. A. S., & Magaia, L. L. (2025). found that Research on multi-step photovoltaic forecasting has also examined transformer-based models and recurrent neural networks using weather observations, weather forecasts, and solar geometry data. The reported results indicated that a transformer model combined with LSTM performed favorably within the study's evaluation setting. Such approaches are promising because renewable energy prediction often involves both short-

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term fluctuations and longer-term dependencies. However, the usefulness of these models must be assessed against strong baselines, realistic forecast inputs, and appropriate evaluation periods rather than relying solely on architectural sophistication.

Solar and wind generation exhibit different physical characteristics, which influence the design and evaluation of forecasting models. Solar photovoltaic production is strongly associated with irradiance, cloud cover, ambient temperature, solar elevation, and daylight duration. Wind power depends on wind speed and direction, turbine power curves, air density, turbine availability, and local atmospheric conditions. Hydropower introduces additional variables, including precipitation, reservoir levels, river flows, and water management policies. As a result, a forecasting model developed for one energy source may not transfer directly to another without changes to the features, training process, and model architecture. The recent literature increasingly recognizes the importance of energy-source-specific model development and evaluation.The 2024 review Recent Advances and Applications of Machine Learning in the Variable Renewable Energy Sector examined supervised and unsupervised learning applications in renewable energy, including energy forecasting, wind turbine monitoring, and energy price prediction. It also discussed performance measures such as mean absolute error, root mean square error, and the coefficient of determination. Similarly, Yang et al. (2024) surveyed machine learning approaches for wind power forecasting, providing a source-specific perspective on the available techniques and their challenges. These studies reinforce the importance of evaluating predictive performance in the context of individual renewable technologies. They also suggest that comparative research should document data resolution, forecast horizon, geographical location, and the characteristics of the energy installation to make its conclusions meaningful.

Hybrid forecasting approaches combine multiple techniques to exploit their complementary strengths. For example, a forecasting pipeline may apply signal decomposition to separate complex time-series patterns before using an LSTM model to predict the resulting components. Another approach may combine a physical weather model with machine learning to correct systematic prediction errors. Ensemble learning combines the outputs of several predictors, while metaheuristic algorithms can search for suitable model hyperparameters or help solve complex operational optimization problems. These approaches are attractive because renewable energy data often contain multiple temporal patterns, nonlinear dependencies, and abrupt fluctuations that a single model may not represent adequately. Nevertheless, hybrid systems may introduce additional computational requirements, parameter sensitivity, and implementation complexity.Recent reviews have examined the combination of artificial intelligence and optimization methods in renewable energy applications. Yu, Y., Ren, W., Mao, L., Ouyang, W., Hu, Q., Yao, Q., ... & Yao, H. (2025). Explained that The survey by A Survey of Artificial Intelligence Methods for Renewable Energy Forecasting: Methodologies and Insights discusses combinations of machine learning and metaheuristic approaches, while the review of artificial intelligence applications in renewable energy systems by Energy Conversion and Management classifies different approaches and their applications. The central implication is that hybridization should be guided by a clear technical objective. If the objective is to improve prediction, the hybrid components should demonstrate lower out-of-sample forecasting errors. If the objective is to optimize energy operations, the evaluation should additionally consider cost, constraints, reliability, and renewable energy utilization. Simply combining several

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algorithms without a controlled comparison does not establish that a hybrid method is superior.

Energy optimization is the process of identifying operational decisions that best satisfy a defined objective while respecting technical and economic constraints. In renewable energy systems, this may involve minimizing electricity procurement costs, reducing battery degradation, increasing self-consumption, minimizing curtailment, or reducing reliance on fossil-fuel generation. Forecasting provides estimates of future renewable output and demand, while optimization uses those estimates to determine an operational schedule. For example, a battery management system can use expected solar production and electricity demand to determine when stored energy should be used or preserved. The resulting schedule may improve system performance, provided that the forecasts are sufficiently reliable and the optimization model accurately represents the relevant operating constraints.Müller et al. (2023) investigated the trade-offs between profitability, complexity, and security in forecasting-based optimization for residential energy management systems. Their work used residential photovoltaic-battery cases and found that gradient-boosted decision tree forecasts could provide a favorable balance between economic benefits and computational complexity in the scenarios studied. The research also highlighted the relevance of input-data security for forecasting-driven decisions. More broadly, the review Artificial Intelligence-Based Methods for Renewable Power System Operation describes how machine learning, deep learning, and reinforcement learning can support forecasting, dispatch, control, and electricity market operations. These findings indicate that optimization should be evaluated as a distinct operational layer, with its own objectives and constraints, rather than as an automatic consequence of improved forecasting accuracy.Uncertainty is a central issue in renewable energy forecasting because weather conditions, equipment availability, and energy demand cannot be predicted perfectly.

METHODOLOGY

The research methodology is designed to investigate the performance of machine learning-based renewable energy forecasting models and their integration with optimization techniques. The proposed study adopts a quantitative, comparative, and computational approach using historical renewable energy generation data, meteorological observations, and electricity demand records. The analysis focuses primarily on solar photovoltaic and wind energy systems because their output is strongly affected by variable environmental conditions and they provide useful cases for evaluating predictive and operational performance. The dataset should include time-stamped power generation, solar irradiance, ambient temperature, humidity, wind speed, wind direction, and electricity demand where available. Additional variables, including precipitation, cloud cover, atmospheric pressure, calendar information, electricity prices, and battery state of charge, may be incorporated according to data availability and the selected optimization task. Data can be obtained from publicly accessible energy repositories, meteorological services, renewable energy monitoring platforms, or electricity system operators, with the source, geographical coverage, measurement frequency, and observation period documented before analysis. Data preparation will involve checking missing values, identifying duplicate observations, correcting inconsistent timestamps, investigating abnormal readings, and aligning measurements from different sources to a common time interval. Missing observations will be handled using methods appropriate to the variable and the duration of the gap, while outliers will be examined to distinguish genuine weather-related events from measurement errors. Continuous variables may be

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normalized or standardized where required by the selected algorithm, with all preprocessing parameters estimated using training data only to prevent information leakage. The forecasting stage will compare a persistence baseline, a conventional statistical baseline where appropriate, random forest, gradient boosting, support vector regression, and an LSTM network.

DATA ANALYSIS

The data analysis will be conducted in several connected stages to establish how input data characteristics, predictive model selection, and optimization decisions influence renewable energy system performance. Initially, descriptive statistics will be calculated to summarize the central tendency, variability, and distribution of the principal variables, including renewable electricity output, solar irradiance, temperature, wind speed, and electricity demand. Minimum values, maximum values, means, standard deviations, missing-data percentages, and temporal coverage will be examined to determine the suitability of the dataset for model development. Time-series analysis will be used to identify daily and seasonal patterns, recurring changes in generation, and periods of unusually high or low production. Correlation analysis may be applied to explore preliminary relationships between meteorological variables and energy output, although correlation will not be interpreted as proof of causation. The analysis will then examine the performance of the forecasting algorithms using the same chronological test period and comparable input information. MAE will measure average absolute prediction errors, while RMSE will give greater weight to large deviations. MAPE may be reported when actual values are sufficiently far from zero, and R2R2 will provide an indication of how much variation in the observed output is explained by the predictions. For datasets containing multiple sites or technologies, normalized error measures will be reported alongside errors in physical units, such as kilowatts or megawatts, to support meaningful comparisons. Performance differences will be examined across forecasting horizons, seasons, and operating conditions rather than relying exclusively on an overall average.

RESEARCH DESIGN

The study will use a quantitative comparative research design supported by time-series forecasting experiments and a simulation-based optimization framework. This design is appropriate because the central research question concerns measurable relationships between forecasting techniques and the operational performance of renewable energy systems. The independent variables will include forecasting algorithm, input-feature configuration, forecast horizon, and optimization strategy, while the dependent variables will include predictive error, operating cost, renewable energy utilization, and relevant storage performance indicators. Dataset characteristics, including geographical location, sampling frequency, installed capacity, and weather conditions, will be documented as contextual variables that may affect model performance. The research will proceed through a structured sequence of data acquisition, preprocessing, exploratory analysis, model development, validation, forecasting evaluation, optimization, and comparative interpretation. Each forecasting algorithm will receive the same eligible training observations and will be evaluated against the same held-out test period to ensure that comparisons are fair. Baseline methods will be retained throughout the study so that the benefits of more advanced models can be assessed against simpler alternatives. Where computationally feasible, repeated rolling-origin

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evaluations will be used to investigate the stability of results over time, and statistical comparisons will be considered when evaluating differences between competing forecasting models. The optimization stage will use a clearly specified objective function and operational constraints so that improvements can be attributed to the forecasting and scheduling strategy rather than to inconsistent assumptions. For instance, the forecast-driven strategy and baseline strategy will be evaluated under the same demand profile, electricity prices, storage capacity, and generation constraints.

FINDINGS

The proposed study is expected to clarify the relative strengths of conventional machine learning, deep learning, and hybrid forecasting methods under comparable experimental conditions. Tree-based methods, including random forests and gradient boosting, may provide competitive results when the dataset contains structured meteorological variables, historical generation measurements, and calendar information. Their comparatively manageable computational requirements could make them attractive for distributed energy systems and smaller renewable installations. LSTM networks may demonstrate advantages when sequential dependencies and changing temporal patterns are important, particularly when adequate training observations are available. Transformer-based and hybrid architectures may offer further opportunities in multi-horizon or multi-source forecasting, although their performance will depend on data quality, model configuration, and the forecasting task. These expectations are consistent with the diversity of methods discussed in recent renewable energy forecasting reviews, but they are hypotheses to be tested rather than findings established by the present draft. A second anticipated finding is that the importance of individual predictors will vary by renewable energy technology. Solar irradiance, cloud cover, solar geometry, and temperature are likely to be relevant for photovoltaic forecasting, whereas wind speed, wind direction, and turbine operating characteristics are likely to be particularly important for wind generation. Historical production and calendar variables may provide additional information about recurring patterns, although their usefulness can diminish when environmental conditions change abruptly. A third expected finding concerns the relationship between forecast accuracy and energy optimization. Better forecasts may enable more effective battery scheduling, reduce avoidable grid purchases, and improve the coordination of renewable generation with demand. However, the magnitude of these benefits will depend on electricity tariffs, battery efficiency, storage capacity, demand flexibility, and the cost of forecast errors. If storage is unavailable or the system cannot alter its operating schedule, improvements in prediction may have only a limited effect on operational costs. Likewise, a model with slightly lower RMSE may not produce a better schedule if its errors occur during periods that have little economic or operational significance.

CONCLUSION

Machine learning-based renewable energy forecasting and optimization represent promising approaches for improving the reliability, efficiency, and sustainability of modern electricity systems. The variability of solar and wind generation creates operational challenges that require accurate prediction, effective resource allocation, and appropriate management of energy storage and electricity demand. This research has outlined a framework for comparing conventional machine learning algorithms, deep learning architectures, and hybrid forecasting approaches using historical generation, meteorological, and demand data. It has

also established the importance of integrating forecasting outputs with optimization techniques so that predictive information can support practical decisions involving battery scheduling, grid electricity procurement, renewable energy utilization, and operating costs. The literature reviewed in this study suggests that the performance of a forecasting model depends on the energy source, prediction horizon, dataset characteristics, input variables, and validation procedure. Accordingly, no single model should be assumed to provide the best performance under all operating conditions. Conventional algorithms may remain effective when data are structured and computational resources are limited, while deep learning models may be useful when sufficient data are available to learn complex temporal relationships. Hybrid approaches can offer additional benefits when their components address specific weaknesses, but their added complexity should be justified by measurable improvements. The proposed methodology emphasizes chronological testing, consistent performance metrics, careful data preprocessing, and the separation of forecasting evaluation from operational optimization. It also recognizes that forecast accuracy alone is not a sufficient measure of practical success.

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