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FULL LENGTH ARTICLE

An AI-Based System for Predicting Renewable Energy Power Output Using Advanced Optimization Algorithms

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ABSTRACT

Accurate forecasting of renewable energy source (RES) generation is increasingly important for effective grid operation and energy management as RES are integrated into electrical grids. Machine learning (ML) and deep learning (DL) algorithms can learn complex relationships from data and provide forecasts, addressing limitations of traditional approaches. This review examines the state of the art and future directions in ML- and DL-based renewable energy forecasting. It surveys the approaches and models used to predict renewable generation and highlights challenges including output uncertainty and variability, data accessibility, and model interpretability. Developing accurate and dependable forecasting models is essential to support the transition to sustainable energy and the integration of RES into electrical grids.

Keywords: Renewable energy ▪ Forecasting ▪ Machine learning ▪ Deep learning ▪ Metaheuristic algorithms ▪ Wind energy ▪ Solar energy

1. INTRODUCTION

Interest in renewable energy sources (RES) has grown with demand for clean, sustainable energy that can reduce greenhouse-gas emissions and help address climate change. RES can also reduce reliance on imported energy, create jobs, and lower costs [1]. However, solar and wind generation vary with weather, sunlight, cloud cover, and wind speed. Accurate forecasting can reduce the operational effects of this variability on electrical systems.

Statistical and physical approaches have traditionally been used to forecast energy generation [2]. Statistical models, including autoregressive integrated moving average (ARIMA), can be limited when data are high-dimensional and contain complex nonlinear relationships. Physical models based on solar radiation and numerical weather prediction (NWP) also face limitations arising from complex and unpredictable weather [3, 4]. Machine learning (ML) and deep learning (DL) offer alternatives because they can learn nonlinear relationships from large datasets and use time-series, meteorological, and geographic inputs [3].

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Prior work has applied hybrid models to solar-radiation forecasting, combining approaches such as artificial neural networks, support vector regression, support vector machines (SVM), and ARIMA. Hybrid models using SVM have also been reported to outperform single predictors in solar forecasting [5, 6]. Wind forecasting studies have explored hybrid SVM models, combinations of ARIMA, extreme learning machines and SVM, adaptive kernel methods, ARIMA and nonlinear autoregressive exogenous models, and metaheuristic approaches [7, 8, 9, 10, 11]. Despite this progress, forecasting accuracy remains affected by model reliability and interpretability, input selection, missing data, and algorithm choice.

This review compares conventional AI-coupled and hybrid AI systems for solar and wind forecasting, summarizes research applying improved metaheuristic methods to energy prediction, and presents directions that can inform future research and practice.

2. LITERATURE REVIEW

Published studies have investigated solar- and wind-energy forecasting to support power-system operation, fault diagnosis, planning, modeling, and monitoring. Existing reviews cover ML, DL, ensemble learning (EL), and hybrid approaches, and discuss both their benefits and limitations. Compared with persistence and NWP models, ML can require less computation but may be more sensitive to noise. Review studies also identify data preparation and cleaning, model bias, and the risk of selecting an unsuitable algorithm as important challenges. Metaheuristic methods can improve prediction performance, although they may increase computation time [12, 13, 14].

Earlier reviews often focused on a subset of AI methods, such as ML, DL, or metaheuristics, or on combinations of two families. The present review considers the AI approaches used to forecast solar and wind power, including hybrid models that combine conventional predictors with metaheuristic algorithms. The surveyed work also motivates recommendations for researchers and practitioners working with renewable-energy forecasting.

1. It compares conventional AI-coupled and hybrid AI systems using metaheuristic techniques for solar and wind RES forecasting.
2. It summarizes research that improves metaheuristic algorithms and applies them to energy-related prediction.
3. It identifies considerations for future research and decision-making in solar and wind energy forecasting.

Table 1 compares representative forecasting studies by site, horizon, application, and reported performance metrics.

3. RENEWABLE ENERGY AND FORECASTING APPROACHES

3.1 Renewable Energy Generation

Renewable sources—including hydropower, solar, wind, biomass, fuel cells, geothermal, and ocean energy—are increasingly used as lower-emission energy sources.

3.1.1 Wind Energy

Wind energy can provide electricity without the emissions associated with conventional generation. In the United States, wind turbines accounted for 8.4% of utility-scale power output in 2020; the source review reports estimates of 20% by 2030 and 35% by 2050. Accurate wind-speed prediction is important for integrating wind turbines into power networks. Data-driven and physics-based methods are both used. Physics-based approaches use atmospheric-motion equations and can be computationally demanding, while conventional time-series approaches such as ARMA can perform poorly when wind speed varies irregularly. AI and metaheuristic methods have therefore also been explored.

3.1.2 Solar Energy

Solar energy is a rapidly growing renewable source, with the source review anticipating production above 8,000 GW by 2050. It describes passive photovoltaic systems as converting DC electricity to AC for buildings and active systems as using concentrated solar power to produce heat for steam turbines. It also notes that silicon-boron solar chips are mainly used in small devices because of their low efficiency. Solar output depends on sunlight and cloud cover, and therefore varies through the day and across seasons. This variability makes reliable production forecasts difficult even when advanced weather forecasts are available. Integrating variable solar and wind generation into existing systems also requires attention to energy storage, transmission capacity, and smart-grid technologies.

3.2 Overview of Forecasting Techniques

Renewable-energy forecasting methods are commonly grouped into persistence, physical, statistical, and AI-based models. Forecasting and high-precision energy monitoring support system development, management, and policy decisions, while the intermittent nature of RES makes data handling and storage important considerations.

Persistence models. These models assume that future values remain similar to current values. They can be useful for short-term forecasts but are less suitable for longer horizons.

Physical models. Solar-panel and wind-turbine forecasts for medium- and long-term horizons can use NWP. Such models may be computationally costly, require substantial computing resources, and have limitations for short-term forecasting.

Statistical models. Statistical approaches map historical time-series data to expected outcomes, often using autoregressive (AR) and moving-average (MA) components. ARMA combines both and is used for short-term forecasts. The review describes comparisons of ARMA and ANNs for wind speed and power, a nonlinear autoregressive (NAR) model for short-term solar-power forecasts, and a small ARMA advantage over ARX. It also identifies ARIMA as a method used for forecasts up to two years ahead, while noting its requirement for stationary data. Statistical approaches are attractive for their affordability and ease of use, including in microgrid energy management.

Table 1. Comparative evaluation of renewable-energy forecasting studies.

Author	Data site	Horizon	Application area	Performance metrics
X. Zhou et al. [15]	North China	Daily	Wind-power forecasting	MAE, RMSE, R
L.-L. Li, X. Zhao et al. [16]	La Haute, France	Hourly	Wind-power forecasting	R^2, RMSE, MAE, MAP
J. Duan, P. Wang et al. [17]	Dingbian, China	5 min	Wind-power forecasting	RMSE, MAE, TIC
A. Rafati, M. Joorabian et al. [18]	Netherlands	Daily	Solar-power forecasting	MAE, MRE, RMSE
R. Yin, D. Li, Y. Wang, W. Chen [19]	CESM	Monthly	Wind-speed forecasting	MAE
G. López and P. Arboleya [20]	Ecuador (Tungurahua)	Hourly	Wind-speed forecasting	R, MSE, MAPE

Artificial-intelligence models. AI methods can learn representations from large datasets and support data mining, clustering, and decision-making. ML, data assimilation, and DL are among the approaches applied to renewable-energy prediction; the following section summarizes the ML and DL methods discussed in the reviewed work.

4. AI-BASED RENEWABLE-ENERGY FORECASTING

4.1 Machine-Learning Methods

ML algorithms learn patterns from data to support prediction and decision-making. The reviewed work describes supervised, unsupervised, and reinforcement learning. Supervised learning uses labeled data to reduce the difference between predicted and observed values, and includes regression and classification. Linear and polynomial regression have been applied to predict solar and wind power generation [21].

Support vector machines analyze historical weather data to identify patterns and forecast wind speed or solar irradiation. They can model nonlinear relationships and are suited to small- and medium-sized datasets. Random forests combine decision trees to improve wind- and solar-power forecasts, help limit overfitting, and handle missing information. Gradient boosting machines improve predictions iteratively by addressing errors in earlier models and can be useful for complex datasets and short-term variation in renewable output.

4.2 Deep-Learning Methods

DL methods can represent complex nonlinear relationships. ANNs learn patterns from large datasets and are used to forecast solar irradiance and wind speed. Convolutional neural networks (CNNs) process image-based data, including satellite images and weather maps, to extract spatial information such as cloud cover. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks model temporal dependencies in meteorological time series, supporting forecasts of future wind speed and solar radiation.

Ensemble approaches can combine predictors such as SVM, random forest, and ANN to aggregate forecasts and reduce errors. Transfer learning can adapt a model trained in one location to another location with limited data, reducing the need to collect a large new dataset. The reviewed solar applications include an ANN model for solar-potential assessment in Himachal Pradesh [22], a CNN–LSTM model for solar-power forecasting [23], a CEEMDAN–CNN–LSTM model for hourly solar-irradiance forecasts [24], and a CNN-based ensemble approach for short- and long-term global horizontal solar irradiance [25].

Figure 1 summarizes the ML, DL, hybrid, fuzzy-logic, and genetic-algorithm method families represented in the source review.

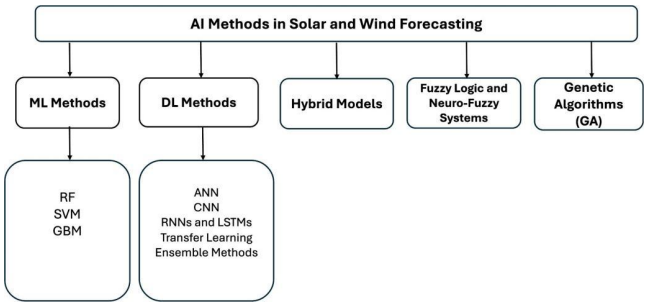


Figure 1. AI methods used in solar- and wind-energy forecasting.

4.3 Ensemble Learning

Ensemble learning combines multiple base learners or weak learners rather than relying on a single model. By using different classifiers, ensemble methods can improve the reliability and accuracy of predictions. The review groups ensemble methods into bagging, boosting, and stacking; stacking combines predictions from base models through a meta-learner [26].

4.3.1 Long Short-Term Memory

RNNs can experience vanishing or exploding gradients when processing sequential data. LSTM networks address this issue through memory cells and input, output, and forget gates that regulate information flow. A hybrid LSTM with Kullback–Leibler divergence has been used to distinguish normal, alarm, and fault conditions in wind-turbine monitoring data. The approach supports early fault recognition, alarm prediction, and SCADA alarm recording; stacked LSTM cells can also be used to predict gearbox-bearing temperatures [27].

4.3.2 Reinforcement Learning

Reinforcement learning (RL) uses policies to choose actions for observed states and seeks to maximize cumulative rewards. In wind-turbine condition monitoring and control, RL can handle multiple variables and actions, including blade operation, pitch angle, and yaw rotation. Actor–critic RL has been applied to optimize control settings while accounting for subsystem interactions. RL can also tune hyperparameters for DL-based condition monitoring, although its black-box nature and substantial training-data requirements remain challenges [28].

4.3.3 Bagging

Bagging creates bootstrap samples, trains multiple base models, and combines their predictions, for example through majority voting. Random forests, extra trees, and random patches are examples. The approach can reduce variance, improve base learners, accommodate diverse inputs, and help

handle missing values. Its use of decision-tree models can, however, make interpretation difficult [29].

4.3.4 Boosting

Boosting iteratively trains base learners, emphasizes examples misclassified by earlier learners, and combines the resulting classifiers according to their performance. It can improve predictive models built from weak learners, but iterative training may overfit, particularly with unstructured datasets [30].

4.3.5 Stacking

Stacking uses predictions from several base learners as input features for a meta-learner. The meta-learner combines those predictions to produce the final output and can reduce generalization errors.

5. CONCLUSION

This review surveys AI methods used to forecast variability in solar- and wind-energy systems. It summarizes the literature on ML, DL, hybrid and metaheuristic methods, and ensemble learning, and presents a conceptual organization of AI approaches for RES prediction. The reviewed studies demonstrate sustained interest in ML and hybrid methodologies for renewable-energy forecasting. Reliable deployment continues to depend on careful data preparation, suitable model selection, interpretability, and attention to the variability of renewable generation.

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