



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

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Abstract

Accurate generation forecasting of Renewable Energy Sources (RES) is becoming more and more crucial for effective grid operation and energy management as RES are incorporated into the electrical grid. Because Machine Learning (ML) and Deep Learning (DL) algorithms can learn complicated relationships from data and provide accurate forecasts, they have become more popular than traditional forecasting approaches, which have limits. This article examines the state of the art and future directions in the field of ML and DL-based forecasting of renewable energy generation. This paper reviews the several approaches and models that have been used to project renewable energy. It also highlights the challenges, such as managing the uncertainty and unpredictability of renewable energy output, data accessibility, and model interpretability. To sum up, this study emphasizes how important it is to develop accurate and dependable renewable energy forecasting models to facilitate the future transition to sustainable energy sources and enable the integration of RES into the electrical grid.

Keywords: Renewable Energy; Machine Learning; Deep Learning

1. Introduction

The focus on RES is heightened due to the growing demand for clean, sustainable energy, which is crucial for reducing greenhouse gas emissions and combating climate change.[1]. So that, RES offers benefits like reducing reliance on foreign energy, creating jobs, and saving money. Solar energy's widespread use faces challenges due to its unpredictable nature including weather and sunlight variations, and its influence on cloud cover and sunlight changes. The problem can be solved by creating accurate forecasting models for the generation of renewable energy. The negative effects of renewable energy generation's unpredictability on the electrical system can be reduced with the aid of precise forecasting models. Traditional forecasting techniques, such as statistical and physical models, have been used for decades to predict energy generation [2]. However, because renewable energy data is high-dimensional and involves complicated nonlinear interactions, statistical models like the auto-

regressive integrated moving average technique have limits [3]. Renewable energy forecasting often uses physical models like solar radiation and Numerical Weather Prediction (NWP), but due to the earth's complexity and unpredictable weather, many models have limitations. To solve these constraints and increase the accuracy of these models, further research and development are needed [4]. Machine Learning (ML) and Deep Learning (DL) algorithms are promising tools for addressing the shortcomings of conventional forecasting methods [3]. ML and DL algorithms are effectively utilized to learn intricate nonlinear correlations from large amounts of renewable energy data due to its high dimensionality. Additionally, a variety of input data types, including time series, meteorological, and geographic data, can be handled by them. Numerous academics have examined the use of ML and algorithms for solar radiation forecasting, which is a key factor affecting solar systems' output power. To improve prediction performance, Voyant et al., for example, proposed using Hybrid Models (HMs) after finding that artificial neural networks, support vector regression, support vector machines (SVM), and auto-regressive integrated moving average are the best methods for predicting solar radiation [5]. In terms of enhancing solar radiation projections, Huertas et al. showed that the HM with SVM performed better than single predictor models [6]. Like solar energy, wind energy, unpredictable and nonlinear, is crucial for energy production due to population growth and rising consumption. Offshore wind farms offer greater access to wind sources and capacity, making them a viable substitute for finite fossil resources. Wind speed data and

Other necessary data are utilised in the creation of wind energy to build models and algorithms for ML and DL. To increase forecast accuracy, several researchers have proposed several models. For example, Zendeheboud et al. [7] introduced hybrid SVM models and suggested that the SVM model was better than other models. For the short-term prediction of wind speed, Wang et al. developed an HM consisting of a mixture of models [8]. The Support Vector Regression (SVR) algorithm performs best when the standard deviation is eliminated from the dataset, according to Demolli et al.'s research, which used five machine learning algorithms to forecast long-term wind power. To improve predicting accuracy, Xiaometal proposed employing a self-adaptive kernel extreme learning machine [9]. Cadenas et al. assessed the ARIMA and nonlinear auto regressive exogenous (NARX) models; they found that the NARX model had reduced error [10]. In other research, a range of models, such as the CNN model, Local Mean Decomposition (LMD), Firefly Algorithm (FA) models, and the Improved Dragonfly Algorithm (IDA) with SVM (IDA-SVM) model, were used to forecast wind power and speed [11]. With the application of ML and DL, the field of renewable energy forecasting has made great progress, yet many problems remain. The accuracy of forecasting models for renewable energy is greatly impacted by several factors, including the need to create reliable and understandable models that can provide insights into the variables that affect the generation of renewable energy. Other factors include the selection of input data, handling of missing data, and ML and DL algorithm choices. The following is the arrangement of the remaining section of this survey article: Section 2 outlines the previous studies. A Synopsis of Renewable Energy Production in section 3. In the 4 section, I will talk about overview of forecasting techniques. The 5 and 6 sections illustrate the impact of ML and DL on the development of renewable energy sources. Further study directions and suggestions are provided in Section 8.

2. Literature Review

The Much published research works on solar and wind energy forecasting address the challenges and responds. These investigations offer strong mechanisms for the electric power systems' fault adaptive operation, diagnosis, planning, modeling, and monitoring. For assisting researchers in locating and summarizing previously published research on the use of AI in building systems, several review papers have been produced. The evaluations identified multiple AI techniques ML, DL, Ensemble EL, and hybrid approaches—that are used to predict the variability of solar and wind renewable energy systems. This research focused on the advantages and difficulties of AI techniques. Among the advantages of the reviews are that, in comparison to the persistence and NWP models, ML is less computationally expensive and more noise-susceptible [12]. Furthermore, it is proven that using DL algorithms always produces superior performance [13]. Nevertheless, those evaluations addressed some of the difficulties AI faces in predicting the variability of renewable energy sources like solar and wind, including data preparation and data cleaning procedures. They made the point that, if the wrong machine learning model is used, the entire process could be rendered ineffective, and that machine learning can occasionally be biased. Furthermore, certain reviews covered the metaheuristic technique used to raise the AI algorithms' performance accuracy. Even so, metaheuristic approaches lengthen the forecasting models' computation times despite their many advantages. The review and survey publications that are now available either concentrate on one aspect of the AI technique or another. While some just considered ML, DL, or metaheuristic techniques, others considered two arms, such as ML and metaheuristic techniques. The most current review, which considered every arm of the AI model for RES, including solar and wind, was released in 2021[14]. The distinctive aspect of this work is that it considers every facet of the AI approach utilized to predict wind and solar power plants. A comparison of the current review studies is shown in table 1. To predict the variability of solar systems' global radiation and wind systems' wind speed, this study will accurately analyze the most recent publications on AI techniques. We will

additionally present a synopsis of the hybrid AI forecasting models, which fuse traditional models and metaheuristic algorithms, and upgraded metaheuristic techniques. Based on research articles that have been published, recommendations are given for the future of solar and wind renewable energy forecasting. This survey has made the following contributions:

1. Comparative studies of conventional AI-coupled and hybridized AI systems with metaheuristic techniques are provided to anticipate solar and wind RES.
2. There hasn't been much study on improving metaheuristic algorithms and using them for anticipating energy-related scenarios. This article presents several research that successfully improved metaheuristic methods and applied them to RES forecasting.
3. Describe possible directions for future study to help practitioners and scholars in the field of solar and wind energy resources make decisions that can be defended.

Table 1: Comparative evaluation of the current review research.

Author	Data Site	Horizon	Application Area	Performance Metric
X Zhou et al. [15]	North China	Daily	Wind power forecasting	MAE RMSE R
LL Li, X Zhao et al.[16]	La Haute France	Hourly	Wind power forecasting	R2 RMSE MAE MAP
J Duan, P Wang et al.[17]	Dingbian China	5mins	Wind power forecasting	RMSE MAE TIC
A Rafati, M Joorabian et al.[18]	Netherland	Daily	solar power forecasting	MAE MRE RMSE
R Yin, D Li, Y Wang, WCESM Chen [19]		Monthly	Wind speed Forecasting	MAE
G López, P Arboleya [20]	Ecuador Tungurahua	Hourly	Wind speed forecasting	R MSE MAPE

2.1 Overview of Renewable Energy Generation

The promise of RES including wind, water, and sunshine for human progress and sustainability has garnered attention for over a decade. The RES include hydropower, solar, wind, biomass, fuel cells, geothermal, and ocean energy are gaining popularity as clean energy sources with fewer greenhouse gas emissions.

1. Wind Energy

In addition to providing clean air and water, wind energy sources don't endanger public safety. With estimates for growth to 20% by 2030 and 35% by 2050, wind turbines in the US accounted for 8.4% of utility-scale power output in 2020. Predicting wind speed accurately is essential for incorporating wind turbines into power networks.

Techniques for predicting wind speed include data-driven and physics-based strategies. While physics-based approaches are computationally demanding they make use of atmospheric motion equations. While they perform better for regular variations in wind speed, conventional time-series approaches such as ARMA deteriorate with irregular variations. To defeat physics-based strategies, meta-heuristic algorithms and conventional AI techniques are being used.

2. Solar Energy

The cleanest renewable energy source is solar energy, which is also rapidly gaining popularity worldwide, according to the Renewable Energy Policy Network. Its production is anticipated to exceed 8000 GWatt by 2050. There are two types of solar energy use: passive and active. To directly employ photovoltaic energy, passive systems convert DC energy into AC for structures. Active generates heat for steam turbines using focused solar power. Solar chips made with silicon boron semiconductors are mostly employed in small devices due to their low efficiency. Buildings to produce renewable energy must first consider factors influencing solar energy output. One problem with renewable energy sources like solar and wind power is that they are inherently unpredictable and fluctuate. Sunlight and wind speeds, which can fluctuate significantly throughout the day and season, are what determine how much power solar and wind power can produce. Even with sophisticated weather forecasting methods, it is challenging to reliably anticipate energy output due to this fluctuation, which creates problems for effectively forecasting energy production. The integration of renewable energy into current systems faces challenges due to variability and unpredictability. Current storage technologies are expensive and limited, but energy storage solutions are necessary. Modernizing transmission lines and smart grid technologies is crucial for a sustainable future.

2.2 Overview of Forecasting Techniques

An overview of different models, approaches, technologies, and AI algorithms is presented in recent research on the forecasting of renewable energy supplies. Renewable energy is the energy source with the quickest growth rate because of global industrialization speeding up the use of fossil fuels. Sustainability and minimal environmental pollution are provided by RES, which include sun, wind, hydropower, biomass, waves, tides, and geothermal. A major obstacle to renewable energy, meanwhile, is still the energy supply. To increase system stability and solve local energy shortages, renewable supply incorporates RES into energy systems. It can be difficult to handle chaotic and sporadic data about RES. Technologies for energy forecasting and high-precision energy monitoring are essential for system development, management, and policymaking. Furthermore, required is appropriate technology for storing renewable energy[7]. The forecast of renewable energy has been approached through ML models; hybrid models have been utilized to improve accuracy, while data-driven models have offered useful techniques. Precise and efficient forecasting is assessed, and different time intervals are employed for distinct objectives. These methods fall into four categories: artificial intelligence, physical models, statistical models, and persistence models

1. Models of Persistence

Persistence models work well for short-term forecasting but are not the best for long-term forecasting since they presume that data values in subsequent phases remain identical.

2. Models of Physical

Medium- and long-term forecasting using NWP-based solar panel and wind turbine models is dependent on numerical weather predictions. They are costly to compute, have trouble with short-term forecasting, and need sophisticated computing equipment. Despite their shortcomings, new approaches have surfaced that perform better than physical models.

3. Models of Statistical

Time series historical facts and expected outcomes are mapped mathematically by statistically based forecasting models. They frequently work in conjunction with autoregressive (AR) and moving average (MA) models and are mostly utilized for short-term forecasting objectives. A popular and highly accurate forecasting tool is the hybrid ARMA model, which combines the best aspects of both AR and MA. The prediction of wind speed and power has been studied between ARMA and Artificial Neural Networks (ANNs). For short-term solar power forecasting, a nonlinear autoregressive (NAR) model was proposed; ARMA outperformed ARX by a small margin. ARIMA is another strong method that can be used for forecasting two years ahead of time; however, it does require stationary data. Researchers are drawn to statistical models because of their affordability and ease of use. They are very helpful in microgrid energy management and anticipating the production of power from renewable sources.

4. Artificial Intelligence Models

The ability of AI-based forecasting models to create strong representations and handle large data fits makes them faster at solving data mining, clustering, and decision-making challenges. Additionally, without explicit programming, they can perform difficult tasks in a reasonably short amount of time. ML, data assimilation, DL, and other methods can all be used under the general heading of AI. The use of ML and DL in renewable energy is covered in detail in sections 5 and 6.

5. Renewable Energy Forecasting using Machine Learning

This section discusses supervised and unsupervised learning algorithms, their variants, and their widespread use in the handling of complicated datasets as well as other ML approaches for renewable energy forecasting. Fig. 1 provides a comparison of several ML and DL methods. ML is a branch of AI that lets machines learn from data and become more efficient. To find patterns in data and make judgments, it entails creating statistical models and algorithms. Applications span commerce, finance, healthcare, and the production of renewable energy. Three types of ML algorithms exist: reinforcement learning, unsupervised learning, and supervised learning. By using labeled data to train a model, supervised learning helps to minimize the discrepancy between expected and actual outputs. Supervised learning algorithms comprise two fundamental subtypes: regression and classification. Two methods for predicting the power production of RES, like solar and wind power, are linear and polynomial regression [21]. Support Vector Machines (SVM): SVMs are a class of algorithms that analyze past weather data to find trends and forecast wind speed and solar irradiation. It can simulate non-linear connections and is efficient with small to medium-sized datasets. To increase forecast accuracy, Random Forests (RF) create an ensemble of decision trees for wind and solar power forecasting. Strong in preventing overfitting and efficient in addressing lacking information. Gradient Boosting Machines (GBM), which are frequently used to forecast short-term variations in solar and wind energy output, are used to improve forecasts by fixing flaws in earlier models. High prediction accuracy; very helpful for intricate datasets.

6. Deep Learning-Based Forecasting of Renewable Energy

A variety of potent tools for improving forecasting of renewable energy are provided by DL techniques. Because of their adaptability in simulating intricate, non-linear interactions, artificial neural networks, or ANNs, are frequently used to forecast sun irradiance and wind speed. Artificial Neural Networks (ANNs) are particularly good at learning from big datasets and identifying complex patterns in the data that aid in precise energy generation forecasting. On the other hand, Convolutional Neural Networks (CNNs) excel at processing image-based data. Through the extraction of spatial information from weather maps and other visual data sources, they analyze satellite photos to anticipate cloud cover, which makes them important for forecasting solar power. Recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks are perfect for capturing temporal correlations in meteorological data because of their time-series forecasting applications. By modeling sequential data, these networks are useful for dynamic forecasting problems, such as predicting future wind speeds or solar radiation levels. By combining several models, like SVM, RF, and ANN, to aggregate forecasts and lower errors, ensemble approaches improve forecasting accuracy even further. Transfer learning also speeds up deployment by allowing pre-trained models to be adapted to different locations with sparse data. For example, a model trained on European solar data can be used for North America. This eliminates the need for large fresh datasets. ANN is a reliable method for estimating solar radiation globally, as demonstrated in a study by Kumar and Kaur [22] in Himachal Pradesh. The ANN-15 model had the best prediction accuracy, demonstrating its potential for determining solar energy potential. A CNN-LSTM model was created by Lim et al. [23] to forecast consistent power generation in solar systems and increase efficiency. For hourly solar irradiance forecasting, Gao et al. [24] suggested a CEEMDAN-CNN-LSTM model that outperformed existing approaches. Using machine learning approaches, Cannizzaro et al. [25] demonstrated a novel method for predicting both short- and long-term worldwide horizontal sun irradiance, producing accurate findings on a real-world dataset. Figure 1 is showing the forecasting methods of the solar and wind field.

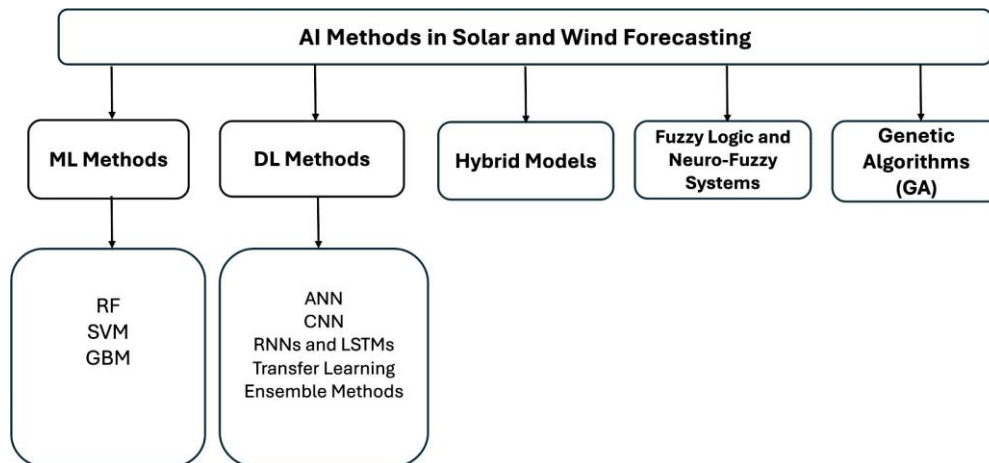


Figure 1. ML and DL Techniques in Renewable Energy.

7. Ensemble learning (EL) Method

Ensemble techniques are ML methods that use weak learners or multiple base learners to solve problems, diverging from traditional methods by developing multiple theories using a single dataset. Compared to conventional machine learning techniques, ensemble methods are more reliable and accurate since they investigate a variety of classifiers, improving prediction models. They are separated into three groups: bagging, boosting, and stacking. Stacking techniques minimize generalization mistakes [26].

8. Long-Short Term Memory (LSTM)

Gradients that disappear or explode are a problem for Recurrent Neural Networks (RNN), which are used to interpret time sequence data. An effective solution to this problem is provided by the LSTM, which makes use of memory cells and three gates: input, output, and forget. Gates manage the data flow between the input and output, and a non-linear function generates the outputs. By examining the patterns and severity of monitoring data, a hybrid LSTM equipped with a Kullback-Leibler divergence model can differentiate between normal, alarm, and fault conditions [27]. This method works better for recognizing faults five days ahead of time, anticipating alarms, and generating SCADA alarm recordings. Condition monitoring data is transformed into information that can be used for anomaly detection by the LSTM network. It is feasible to anticipate gearbox bearing temperatures using a stacked long-short-term memory model with numerous LSTM cells.

9. Reinforcement learning

Reinforcement Learning (RL) is an algorithm that uses rules and policies to learn actions for internal states and related actions. Through increased reward collection, it seeks to maximize the ideal action-value function. To condition monitoring of WT, RL is most effective when used on sparse datasets. It also handles more than one control and optimization application. Because RL [28] algorithms consider multiple variables and actions, they can monitor and manage wind turbine blades, pitch angles, and yaw rotations. Wind power absorption and system efficiency are enhanced by this learning-based monitoring. Regarding energy variation from rated power, new algorithms for updating policies and reward schemes are suggested. The suggested method, Actor-Critic-RL, optimizes control settings while taking subsystem interactions into account. Deterministic forecasting accuracy is increased in WT condition monitoring by optimizing the hyperparameters of existing DL techniques using RL algorithms. However, RL algorithms show durability and dependability in WT condition monitoring, despite their "black box" nature and large training data requirements.

10. Bagging Method

To enhance the performance of machine learning models, Breiman created the bagging ensemble method [29] in 1994. With this approach, random samples are created, and the final findings are combined by majority vote. Through the creation of bootstrapped duplicate features, diversity is achieved. An Extra Tree classifier, Random Forest, and Random Patches are all part of the bagging technique. Less computing cost, controlling missing values, boosting base learner performance, reducing variation without compromising bias, and managing input data diversity are some advantages. However, bagging EL has interpretability difficulty due to the use of decision tree algorithms. The boosting EL method converts a collection of weak learners into a robust classifier. Iteratively engaging base learning algorithms with modified input datasets is the fundamental clue to boosting. A linear combination of several base classifiers weighted according to their quality efficiency is the final model that was

produced. Low variance and high bias base learning methods can be handled by boosting to create a low variance and low bias predictive model.

11. Boosting Method

An artificial intelligence technique called the boosting EL method turns ineffective learners into reliable classifiers. It involves iteratively engaging base learning algorithms to modify input datasets, training, predicting, and selecting misclassified samples from a weak learner. Various basic classifiers are combined linearly and weighted according to their quality performance to create the final model. By using boosting, low variance and high bias base learning algorithms can be handled, resulting in a low variance and low bias prediction model. However, it struggles with unstructured datasets due to overfitting due to the iterative learning technique [30].

12. Stacking Method

An EL method called stacking teaches ML algorithms to aggregate predictions from various methods. By using base learners' predictions as input metadata to a meta-learner, which subsequently trains meta-classifiers to provide final prediction results, it lowers generalization mistakes associated with ML problems.

3. Conclusion

Numerous research has utilized the AI model to show how well it can anticipate the variability of renewable energy sources like solar and wind. To forecast the variability of solar and wind energy systems, this study analyzed the literature on AI methodologies. This study reviewed the literature on AI techniques investigated for solar and wind energy system variability forecasting. A conceptual framework for AI for RES prediction as well as a taxonomy of various AI techniques were offered. The surveyed papers revealed their predicting methodology and comparisons. Each article that was surveyed provided insights that were shared. There were talks and suggestions for further work based on the papers. It was found that the prediction of solar and wind renewable energy variability is attracting a lot of interest in machine learning and its hybrid methodologies.

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