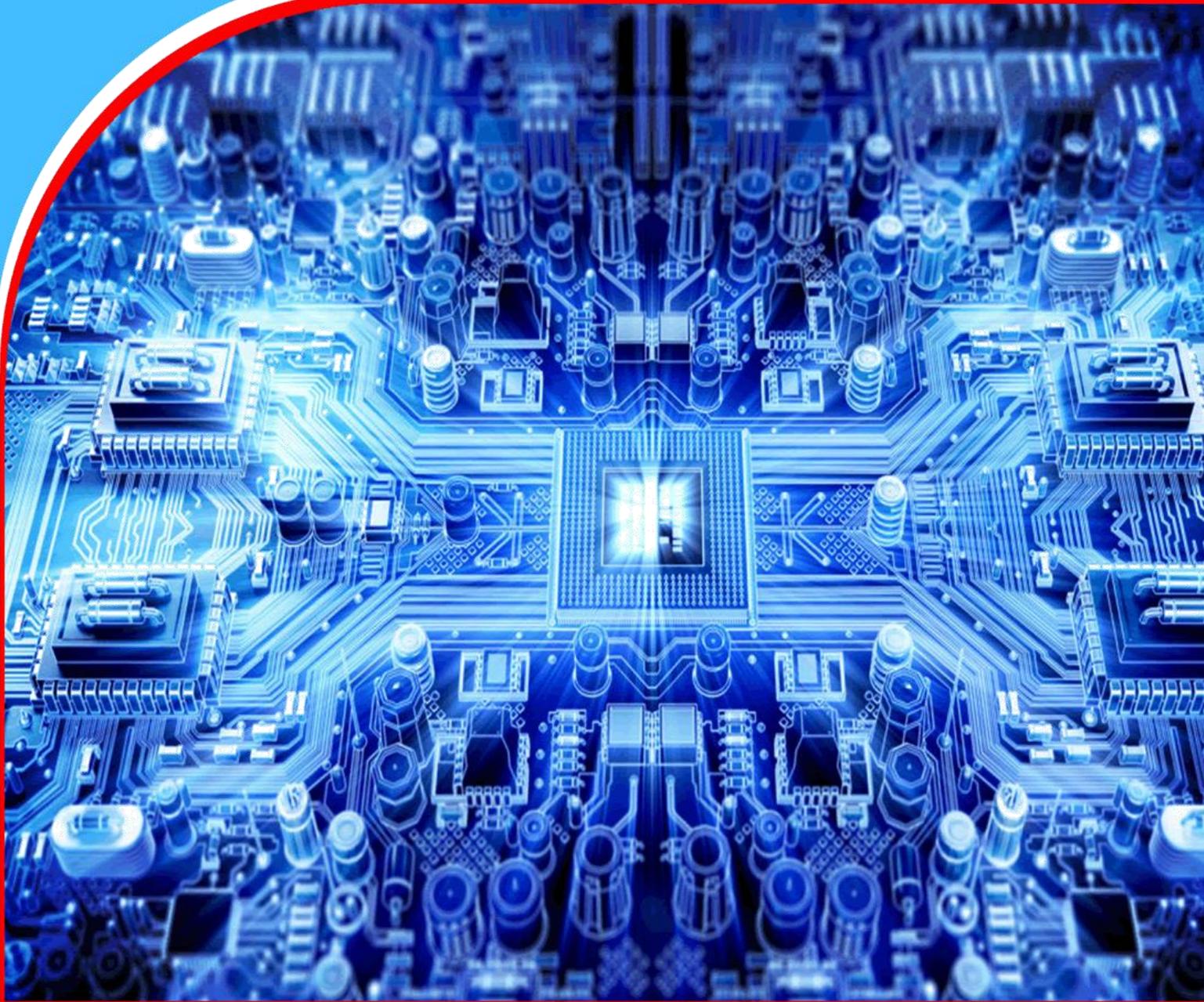
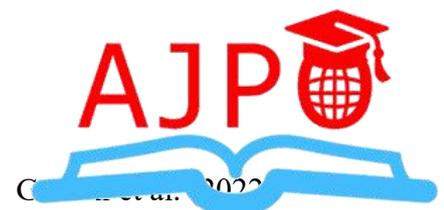


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**Wind and Solar Power Generation Forecasting Using  
Hybrid Deep-Learning Models**

Krishna Gandhi, Pankaj Verma



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## Wind and Solar Power Generation Forecasting Using Hybrid Deep-Learning Models

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### Article history

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### Abstract

**Purpose:** The extensive adoption of wind and solar energy into the contemporary power systems has enhanced the relevance of precise and dependable forecasting of the generation. Such variability, nonlinearity, and uncertainty of renewable resources are a major challenge to conventional forecasting methods, which encourages the use of the modern data-driven methods. The purpose of this review is to be a resource to those researchers and practitioners interested in advancing the renewable energy forecasting methods.

**Materials and Methods:** Deep-learning models have shown great potential in learning complex temporal and spatial patterns in renewable energy data in recent years, but independent deep-learning methods typically have drawbacks including noise sensitivity, overfitting, and lack of interpretability. In a bid to ensure these problems are solved, hybrid deep-learning forecasting models have come up as a promising solution to these problems because they combine deep learning with signal decomposition, machine learning, fuzzy systems, optimization algorithms, and physical knowledge. The review is a coherent and topical analysis of hybrid deep-learning models of the forecasting of wind and solar

power generation. It talks about fundamental knowledge of forecasting, popular deep-learning designs and significant strategies of hybridization such as decomposition-based, machine learning, deep learning, fuzzy models and optimization models. Applications to wind and solar forecasting are examined in more detail, including deterministic, probabilistic and spatial forecasting applications. A comparative dialogue points out performance traits, computation concepts, and resource-specific modelling behaviour.

**Findings:** Lastly, the main issues, areas of research interest and the future research directions are established so as to assist in coming up with more vigorous, interpretable and operationally feasible hybrid forecasting models.

**Unique Contribution to Theory, Practice and Policy:** The review is a coherent and topical analysis of hybrid deep-learning models of the forecasting of wind and solar power generation.

**Keywords:** *Wind Power Forecasting; Solar Power Forecasting; Hybrid Deep Learning; LSTM; CNN; ANFIS; EMD; Wavelet Transform; Renewable Energy Forecasting*

## INTRODUCTION

The growing use of wind and solar energy as part of the contemporary power network has changed the entire direction of the manner in which electricity is produced, distributed, and controlled [1]. Indeed, compared to traditional sources of generation, wind and solar energy are both inherently variable and are also subject to changes due to weather conditions, a factor that has necessitated predicting its availability with a high level of accuracy as a key consideration to the successful operation of the power system. Accurate generation predictions can be the main focus on grid stability as the operator is given the possibility to match the supply and demand on the spot and resolve frequency variances that can occur as a result of abrupt changes in renewable generation [2].

It is also necessary to have quality wind and solar forecasting to the proper running of the energy market. The error in forecast has a direct impact on the bidding strategy, the market clearing price, and imbalance costs, which consequently influence the economic performance of the power producer and the system operator [3]. Moreover, forecasts of good quality can be used to make the decisions of unit commitment and economic dispatch so that traditional generators and storage systems can be more effectively scheduled to keep the cost of operation lower as well as the reserve level.

Nonetheless, Traditional persistence-based, or linear, statistical, predictions models derived through the autoregressive integrated moving average models have little ability to describe in detail the nonlinear, nonstationary, and nonlinear dynamics of wind velocity and solar energy levels [4]. Such techniques are commonly vulnerable to fast changing weather patterns and do not generalize effectively to new locations and regimes of operation. Figure 1 has indicated that the high rate at which renewables are penetrating has increased the forecasting demands, which has highlighted the necessity of using more sophisticated and stronger forecasting approaches.

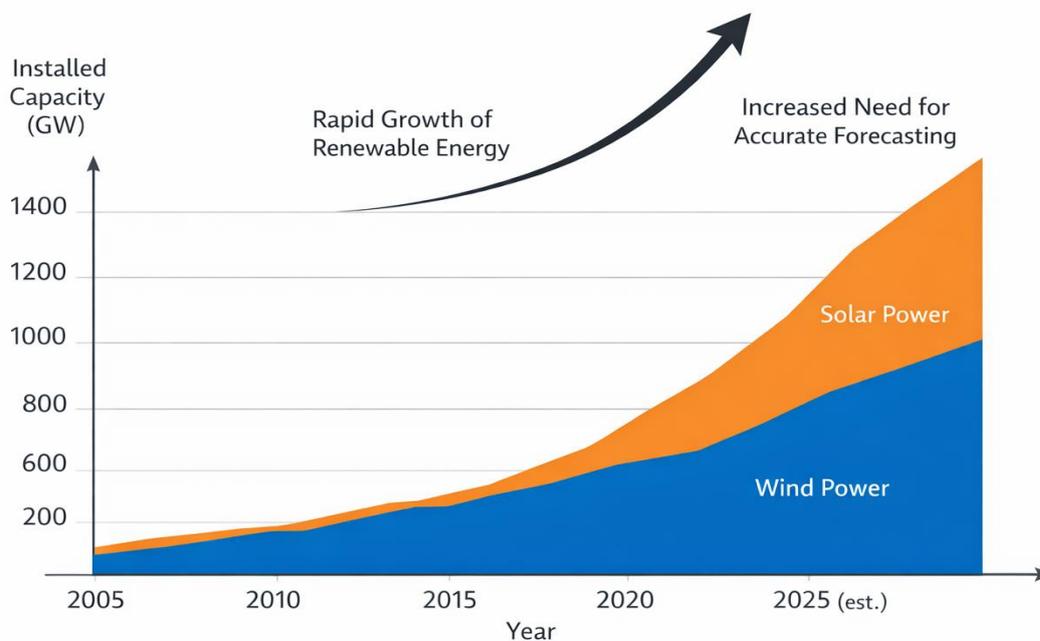


Figure 1: Growth of Global Installed Capacity of Wind and Solar Over time

There are a number of intrinsic complications which are linked with wind and solar power forecasting due to the nature of the renewable resource and the way it interacts with the atmospheric processes. Intermittency and non-linearity are one of the main challenges, as the speed of wind, as well as the output of solar panels [5], is continuously changing and has complicated dynamics with the corresponding generated power at the cut-in, rated and cut-out points, or under partially sunny conditions with photovoltaic systems.

The other important issue is whether uncertainty that is caused by faults in meteorological measurements and numerical weather forecasts [6]. Even the slightest change in the quality of wind velocity or cloud cover can result in powers that are overestimated or underestimated disproportionately. It is an uncertainty that would be intensified when there is an extended length of forecasting and an extreme or fast altering weather.

Also, spatial-temporal variability is very important in forecasting renewable generation [7]. Even in a relatively small area, wind and solar resources are not only seasonally different, but also geographically. This location dependence makes it difficult to predict sites where the model was not trained and restricts the applicability of models in a different location. Table 1 gives a comparative summary of these issues in wind and solar power forecasting and identifies common and resource-specific challenges.

**Table 1: Comparison of Forecasting Challenges in Wind Vs Solar Power**

Aspect	Wind Power Forecasting	Solar Power Forecasting
Primary variability source	Wind speed and direction	Solar irradiance and cloud dynamics
Non-linearity	High, especially near turbine operating limits	High due to irradiance–power conversion
Weather sensitivity	Strongly affected by atmospheric pressure and turbulence	Highly sensitive to cloud cover and aerosols
Spatial dependency	Significant due to terrain and wake effects	Moderate to high due to cloud movement
Forecasting complexity	High for both short- and long-term horizons	High for short-term horizons

Wind and solar power forecasting methods have developed considerably over time due to the rise of penetration of renewables and the complexity of the system itself [8]. Earlier methods are based extensively on persistence models which hold that further power production will be near to the recent observations. Although also simple and computationally efficient, persistent models will only perform reasonably well with very short horizons.

After that, statistical models like linear regression and autoregressive models were introduced to be able to incorporate historical trends and time dependent effects [9]. Despite the fact that these techniques performance was much better than that of persistence techniques in relation to accuracy of the forecasts, they also had nonlinear assumptions imposed on them which restricted their success in nonlinear forecasts.

The development of machine learning methods, such as artificial neural networks and support vector regression, was a significant breakthrough since it allowed nonlinear modeling of the

relationship between input variables and power output. Recently, deep learning models have shown better performance due to their automatic ability to extract hierarchical features in big and complex data sets. In spite of these advances, standalone deep learning models could still possess drawbacks, including overfitting, noise sensitivity, as well as lack of interpretability. These shortcomings have inspired the discovery of hybrid forecasting models which integrate deep learning, signal processing, or other machine learning methods to increase robustness and accuracy.

The hybrid deep-learning models reviewed in the given work have been specifically created in the field of wind and solar power generation predictions [10]. It is also constrained to strategies of modeling and architectures that have been researched in the literature and brought to maturity, thus offering a holistic and well-developed view on the topic. Accurate forecasting of wind and solar power generation remains a challenge due to intermittency, nonlinearity, spatial-temporal variability, and uncertainty in meteorological inputs. Existing forecasting models, including standalone deep learning approaches, often suffer from noise sensitivity, overfitting, limited interpretability, and poor generalization across sites. This study addresses these gaps by reviewing hybrid deep-learning models that combine multiple techniques for enhanced accuracy and operational applicability. The beneficiaries of this study include grid operators, renewable energy producers, and researchers in renewable energy forecasting and smart grid management.

This review has threefold main contributions. To begin with, it presents a structural classification of hybrid deep-learning models, dividing them into various groups according to structural design and integration strategies. Second, it provides the comparative analysis of various hybrid methods, their strengths and limitations, and the situations of their usage in wind and solar forecasting. Lastly, the review reveals the main gaps of research and issues which have not been solved, which provides insights about the areas where the methodological advances and the validation of the issues are expected.

## **Wind and Solar Power Forecasting Fundamentals**

### **Forecasting Horizons**

The forecasting horizons are often classified according to the time between forecasts production and the prediction [11]. The different horizons have different operational and planning roles in power systems and different modelling strategies are needed because of the degree of uncertainty and availability of data.

#### **Very Short-Term Forecasting (seconds–minutes)**

Very short-term forecasting is concerned with forecasting timescale ranging between a few seconds to several minutes into the future. The main areas of application of these forecasts are in real-time grid control, frequency regulation and ramp-rate mitigation. Recent historical measures and sensor data on high resolution dominate at this horizon and persistence-based methods tend to give a solid foundation. Yet, sophisticated, data-driven models are finding a growing use to capture quick variations due to turbulence in wind areas or by a rapidly evolving cloud cover over solar irradiance.

#### **Short-Term Forecasting (hours–days)**

Short time forecasting refers to time intervals ranging between a few hours to a few days in future and is an important aspect of market activities, unit commitment, and economic dispatch [12]. In this horizon, weather processes play a very big role in forecast accuracy, and the application of weather knowledge is very crucial. At this level, both wind and solar predictive

models need to strike a balance between time learning of power data and exogenous weather data. This range is where deep-learning models with a hybrid architecture can be particularly effective: they can be enhanced with feature extraction and temporal dependency modeling techniques, as well as noise reduction.

### Medium- and Long-Term Forecasting (weeks–years)

Medium and long-term forecasting take care of several weeks to several years of a horizon and they are primarily applied in maintenance planning, resource evaluation and capacity expansion investigations. Such predictions are based more on climatological patterns and long-term weather statistics as opposed to high-frequency data. Although less frequently used in such horizons, hybrid methods that combine a statistical analysis and learning methodologies were investigated to enhance the forecasting of trends and the quantification of uncertainty. Table 2 gives a summary of forecasting horizons, common model use applications and common models.

**Table 2: Forecasting Horizons, Applications, and Commonly used Models**

Forecasting Horizon	Time Scale	Key Applications	Commonly Used Models
Very short-term	Seconds–minutes	Frequency control, ramp-rate limitation	Persistence, ANN, LSTM
Short-term	Hours–days	Energy markets, unit commitment, dispatch	ANN, CNN, LSTM, hybrid DL
Medium-term	Days–weeks	Maintenance scheduling, resource planning	Statistical models, ML
Long-term	Months–years	Capacity expansion, policy analysis	Statistical and climatological models

### Input Variables and Data Sources

Wind and solar power forecasting models greatly rely on the quality of the input data, based on its relevance [13]. Common forecasting inputs encompass weather variables, numerical weather model outputs, and historical energy readings which are received within working systems.

### Meteorological Variables

Both wind and solar forecasting models are based on the meteorological variables [14]. In wind power forecasting, such important variables are the wind speed of a wind and the direction of wind, and they are what directly relate to the power output of turbines. Other parameters like temperature of air and atmospheric pressures are other factors that manipulate the air density, which in turn affects the energy production. Global horizontal irradiance, direct normal irradiance, ambient temperature, and cloud indicators are important input elements in solar power forecasts because they determine the photovoltaic conversion efficiency and extremes.

### Numerical weather prediction (NWP) data

The NWP Meteorological conditions give forecast data on meteorological variables at different spatial and time scales [15]. Large forecasting models used NWP, including those generated by global and regional forecasting centers, provide wind speed, irradiance, temperature and

pressure predictions which can be used as key inputs in short- and medium-term power prediction. Although NWP data can improve the lead time of the forecast, they also bring the uncertainty of using the model as approximations and the effects of spatial averaging and require post-processing with machine learning or hybrid deep-learning models.

### **History Power and SCADA Data.**

Power output records in history and supervisory control records and data acquisition measurements give a firsthand insight of how the system will behave at various operating conditions. These datasets reflect the site-specific data, such as power curves of turbines, shading, and deterioration of equipment. Historical power data, combined with meteorological data, can be used to then train data-driven models in order to learn the complex relationships between inputs and outputs and gain a better forecast.

### **Performance Evaluation Metrics**

The performance of wind and solar power forecasting models is commonly evaluated using statistical error metrics that quantify the deviation between predicted and observed power output. Widely used metrics include mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and normalized root mean square error (nRMSE). Each metric highlights different aspects of forecast quality, such as sensitivity to large errors or relative performance across different power scales.

In addition to absolute error metrics, forecasting performance is often assessed using skill scores, which compare the accuracy of a given model against a reference benchmark, typically a persistence model. Skill scores provide a normalized measure of improvement and are particularly useful for evaluating the added value of advanced or hybrid forecasting approaches.

An equation block defining these metrics can be included in this section to formally describe their mathematical formulations and ensure clarity and reproducibility.

### **Overview of Deep-Learning Models for Renewable Forecasting**

Deep-learning models have also been popular in wind and solar power prediction because they possess capabilities to represent complex nonlinear association and temporal associations of renewable power information. This section gives a review of the most widely utilized deep-learning structures that are the building blocks of hybrid forecasting models.

#### **Artificial Neural Networks (ANN)**

One of the first deep-learning-based methods to forecast wind and solar power is based on artificial neural networks [16]. The simplest Feed-forward ANNs are made with an input layer, one or more hidden layers, and an output layer, and the nonlinear activation functions allow the modeling of more complex input/output relationships. Rear schedules in initial research on renewable forecasting ANN models were learned on meteorological variables and historical power data to forecast generation in the future. Whereas ANN-based methods showed better results when compared to first-order statistical models, their inability to capture time-dependent dynamics and reduced sensitivity to input noise inspired the development of more sophisticated deep-learning systems.

#### **Convolutional Neural Networks (CNN)**

Convolutional neural networks have been offered in the research of renewable energy forecasting mainly because of their robust feature extraction. CNNs were initially created to

process image tasks but have been modified to work with unidimensional and 2D arrays in the applications of wind and sun energy.

CNN-based algorithms are typically used to extract features of time-series, with convolutional filters that extract local time-dependent variations in wind-speed, irradiance or power output time-series. CNNs have also been successfully applied to spatial weather maps (e.g. irradiance distributions, or gridded wind fields) where spatial correlations between the various geographical locations can be learned.

An overview CNN architecture used in the context of renewable energy prediction is shown in Figure 2 where the convolutional, pooling layers are used to extract meaningful features to the regression layers which produce power predictions.

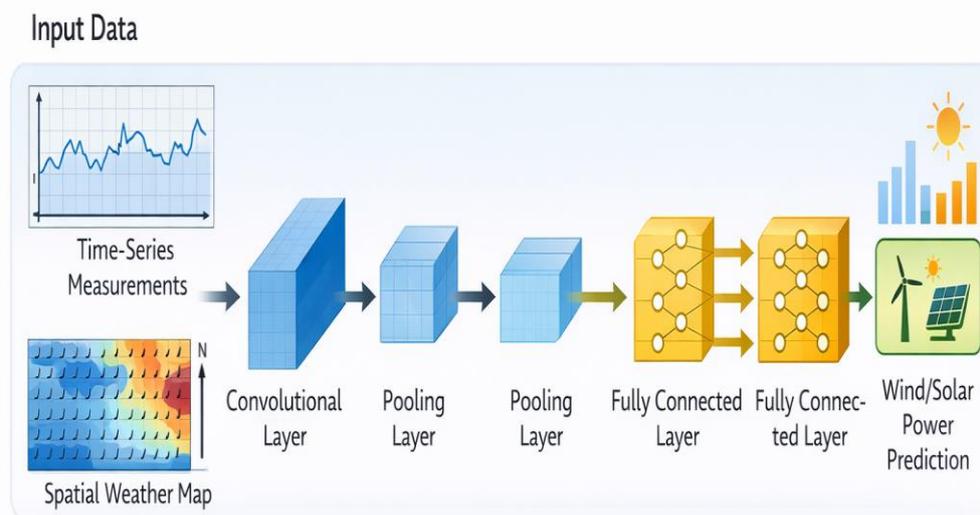


Figure 2: CNN-Based Renewable Energy Forecasting Pipeline

### Recurrent Neural Networks (RNN)

The recurrent neural networks are made with a particular purpose of modeling the sequential data by deploying the feedback connections as such that enable the information to be persistent over the time. Such property contributes to the fact that RNN-based architectures are especially applicable in the field of wind and solar power forecasting where time-based relationships are quite important.

#### Standard RNN

Conventional RNN models have a hidden state which gets updated at each time step depending on the input of the current state and the previous state [17]. Despite the effectiveness in short sequences, the main problems associated with standard RNNs include vanishing and exploding gradients, which restrict its capability to learn long-term dependencies in time series in renewable energy.

#### Long Short-Term Memory (LSTM)

Long short-term memory networks overcome these shortcomings of regular RNNs by adding gated processes that control the flow of information in memory cells. These gates also allow the use of LSTM models to identify short-term variability and long-term trends in the data of wind speed and solar irradiance. Consequently, LSTM-based forms have now been popularly used as models that predict renewable power more so in short time scale forecasting processes.

### Gated Recurrent Unit (GRU)

Gated recurrent units provide an easier variant of LSTM networks as the input and forget gates are integrated into one update gate [18]. GRU models have the capability to model temporal dependence and decrease computation complexity. GRU-based models typically perform just as well as LSTM networks in wind and solar forecasting, particularly when the data used to train them is scarce as it is. A comparative overview of RNN-based architectures that are widely present in renewable forecasting is given in Table 3.

**Table 3: Comparison of RNN, LSTM, and GRU for Wind/Solar Forecasting**

Model	Key Characteristic	Strengths	Limitations
RNN	Basic recurrent structure	Simple architecture	Difficulty learning long-term dependencies
LSTM	Memory cells with gating mechanisms	Strong temporal modeling capability	Higher computational cost
GRU	Simplified gated structure	Efficient training and good performance	Slightly reduced flexibility compared to LSTM

### Autoencoders and Deep Belief Networks

Deep belief networks and autoencoders have been used in forecasting of renewable energy majorly to reduce features and deal with noise. Autoencoders are trained to extract smaller representations of input data by compressing the data onto a lower dimensional latent space and decompressing the data to the output. With such an ability, they can be used to denoise meteorological input and eliminate redundancy in high-dimensional data.

Wind and solar forecasting problems have also been solved using deep belief networks, which consist of layered restricted Boltzmann machines, to learn hierarchical features. They are not as widely used as CNNs and RNNs, but these models have been shown to have potential in enhancing the quality of forecasts when used in conjunction with other learning structures. Their use in renewable projections has mainly presided on improving feature representation before the regression or temporal modeling processes.

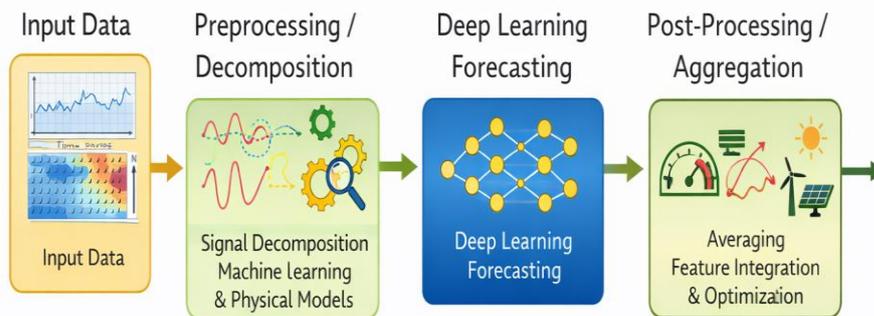
### Hybrid Deep-Learning Forecasting Models

A strong category of forecasting methods has also proven to be a hybrid deep-learning where modeling paradigms are combined to address the limitations of individual methods [19]. In the area of wind and solar power forecasting, it has been proposed to enhance the performance of forecasting techniques using signal processing, machine learning, optimization, and physical understanding, coupled with deep-learning networks.

### Concept and Motivation of Hybrid Models

The main reason that prompted the development of hybrid forecasting models is that the information about renewable energy is complex and nonstationary. Single-model methods tend to fail to capture noise, nonlinearity as well as a temporal dependency. Hybrid models are models that are trying to ease these difficulties by breaking down the forecasting task into digestible parts and allocate specialized techniques to the parts.

Hybrid e.g. deep-learning models Hybrid The hybrid e.g. deep-learning models typically integrate signal decomposition and deep learning, with the raw input signals first broken down into simpler subcomponents, which in turn are represented by neural networks. The other method that has been widely combined is machine learning and deep learning where the standard models of learning do feature-selection or preprocessing, but deep learning networks do not. Also, physical and deep-learning model architecture uses domain knowledge, e.g. power curve relations, irradiance modeling, etc. to constrain or direct the data-driven learning process, as presented in Figure 3.



**Figure 3: Generic Hybrid Renewable Energy Forecasting Framework**

### **Decomposition-Based Hybrid Models**

The use of decomposition-based hybrid models has been one of the most popular techniques in wind and solar forecasts. These models are designed to minimize the complexity of data by breaking down original signals into a number of components with different frequency properties that separately are modeled by using deep-learning applications.

### **Wavelet Transform and Deep Learning**

Hybrid models using the wavelet transform represent signals of wind speed or solar irradiance in a number of frequency bands, as a result of time-frequency analysis [20]. Noise and the rapid fluctuations are normally recorded in high-frequency components resembling those that would be found in the low-frequency components as a result of underlying trends. These degraded signals are then fed as inputs to the deep-learning models like feed-forward neural networks or recurrent models. Hybrid networks WT-ANN and WT-LSTM have become useful in that the network can forecast with an enhanced level of performance due to the presence of noise reduction and multi-resolution analysis which permit deep networks to learn more informed patterns and which are less volatile.

### **Empirical Mode Decomposition (EMD) Variants**

The methods of empirical mode decomposition are adaptive and break down nonlinear and non-stationary signals into intrinsic mode functions. The EMD-LSTM is a hybrid model that uses this decomposition to model the individual intrinsic components independently then combine the findings. Ensemble-based schemes also lead to increased decomposition stability through less mode mixing as well as complementary ensemble schemes lead to an increase in reconstruction accuracy. With CNN or LSTM architectures, these decomposition strategies have demonstrated a high level of ability in both short-term variation and long-term patterns in renewable power data. Table 4 gives a comparative summary of some of the commonly used decomposition-based hybrid models.

**Table 4: Summary of Decomposition-Based Hybrid Models**

<b>Decomposition Method</b>	<b>Deep-Learning Model</b>	<b>Key Advantage</b>	<b>Application</b>
Wavelet Transform	ANN	Multi-resolution feature extraction	Wind power
Wavelet Transform	LSTM	Noise reduction with temporal modeling	Solar power
EMD	LSTM	Adaptive signal decomposition	Wind power
Ensemble EMD	CNN	Improved stability and feature learning	Solar power
Complementary EMD	LSTM	Enhanced trend and fluctuation modeling	Wind power

### Machine Learning and Deep Learning Hybrids

Machine learning and Deep-learning hybrid representations combine the capabilities of conventional learning functions with sophisticated neural networks. The aim of these models is to better represent the features and minimize the complexity of the model as well as increase the accuracy of the forecasting.

#### ANN / SVR + LSTM

Shallow learning methods are commonly used in ANN or support vector regression with LSTM models to learn first features, reduce the dimension, or nonlinear regression methods [21]. The extracted characteristics will be forwarded to LSTM networks to do the temporal modeling to capture sequential relationships in wind velocity or solar irradiance records. This two-step framework assists in enhancing the model generalization and offers decreased sensitivity to the input noise.

#### Random Forest + Deep Learning

Random forest model is typically applied to hybrid frameworks to determine feature importance, and initial regression or classification. The selected features or the results of the random forest are then used as inputs to deep-learning models to do another round of small forecasting. This strategy builds the interpretability and strength of ensemble tree techniques and takes advantage of the characterization acquisition ability of in-depth neural networks.

#### Fuzzy and Neuro-Fuzzy Hybrid Models

Fuzzy and neuro-fuzzy hybrid models are particularly suitable for handling uncertainty and imprecision in renewable energy forecasting. These models combine rule-based reasoning with learning-based adaptation to better represent the nonlinear behavior of wind and solar systems.

#### ANFIS + Deep Networks

Adaptive neuro-fuzzy inference systems that are built into deep-learning structures provide a significant hybrid architecture to renewable forecasting. ANFIS components in these types of models can be deployed to manage uncertainty with the help of fuzzy membership functions and linguistic rule integration, whereas deep neural networks would be able to capture nonlinear and temporal interactions that are complex. This hybridization enhances good

interpretability and strength particularly when there is uncertainty or quickly changing weather conditions. The structure of an ANFIS–deep learning hybrid forecasting model is illustrated in Figure 4.

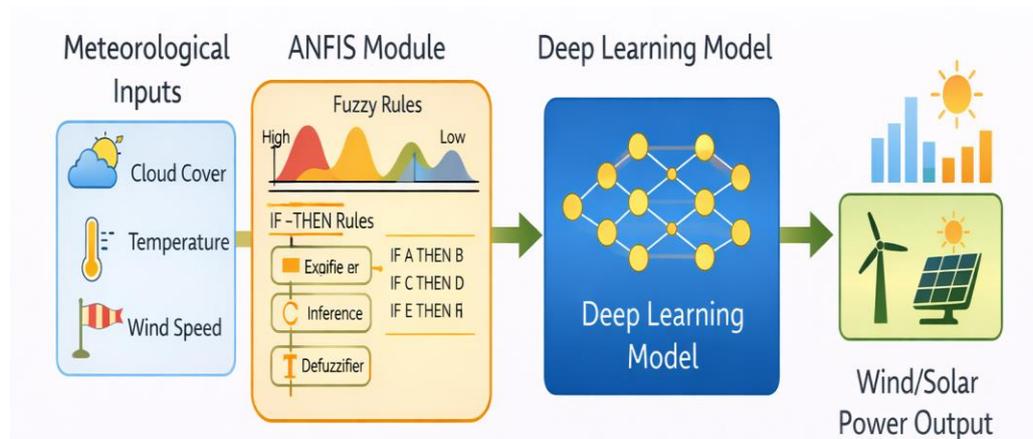


Figure 4: ANFIS - Deep-Fuzzy Hybrid Forecasting Model

### Optimization-Based Hybrid Models

Hybrid models based on optimization can improve the performance of deep-learning by optimizing hyperparameters [22], the weights, or the structures through population-based optimization algorithms. The objectives of these methods are local minimum avoidance and better convergence.

#### Deep Learning Genetic Algorithm (GA) Optimization

The problem of genetic algorithms optimizing the parameters of the neural network such as learning rates, the number of hidden neurons and weight initialisation is frequently seen. Deep-learning models, optimized by GA, are more effective at finding solutions in prediction, because they can be evolved to a broad solution space with the use of evolutionary operators.

#### Particle Swarm Optimization (PSO)

Particle swarm optimization is an algorithm that uses the collective search behavior to narrow deep-learning parameters [23]. The hybrid models based on PSO are computationally efficient and useful in balancing exploration and exploitation processes in optimization.

#### Grey Wolf Optimizer (GWO)

Grey wolf-inspired optimizer-hybrid: Based on social hierarchy and hunting behavior, the hybrid models are used to optimize deep-learning settings. To enhance both the convergence speed and model robustness these models have been utilized to forecast renewable. A table 5 provides a summary of the optimization techniques used in addition to deep-learning models.

**Table 5: Optimization Techniques Used with Deep-Learning Models**

Optimization Technique	Optimized Parameters	Key Benefit
Genetic Algorithm	Network structure, weights	Global search capability
Particle Swarm Optimization	Learning rate, weights	Fast convergence
Grey Wolf Optimizer	Hyperparameters, weights	Balanced exploration and exploitation

### Hybrid Models for Wind Power Forecasting

The hyper-combination of deep-learning models has widely been used in wind power forecasting to solve the problem of nonlinear, stochastic, and spatially dispersed wind resources. Compared to the signal decomposition, feature extraction and time model approaches, these hybrid methods have shown greater accuracy and strong performance on a range of forecast scenarios.

#### Short-Term Wind Power Forecasting

One of the most active spheres of hybrid deep-learning models applicability is short-term wind power forecasting, which is directly related to the activities of power systems and their market involvement. Forecasting models in this horizon should successfully capture the wind speed fluctuations which may change in the atmosphere quickly but still have to remain stable at such changes.

The EMD-LSTM models are among the dominating architectures that break down the wind speed or power signals into intrinsic parts that models the various frequency behaviors. The LSTM networks are then used to model each component where the hybrid framework is able to address short-term volatility as well as long-term temporal dynamics. The method is less sensitive to noise and it enhances the effect of forecasting during turbulent winds.

CNN-LSTM models have also become popular in short-term prediction of the wind [24]. Time series wind speed Convolutional layers are used in these models to find meaningful local features in wind speed time series or space wind fields, whereas LSTM layers describe the temporal dependencies of these features. This synergism allows successful learning of the vast combinations of the rapid changes of winds and contact of the wakes.

These hybrid deep-learning models have been tested on diverse onshore and offshore scenario case studies and it has been proven that it is flexible to changing terrain features and atmospheric processes. Onshore sites demand powerful capabilities against greater turbulence and spatial heterogeneity and offshore environments in specific cases are good due to the easy wind profiles and intense temporal correlations.

#### Probabilistic Wind Forecasting

Besides the point forecasts, probabilistic wind power forecasting is receiving increased interest since it is capable of giving useful information about the uncertainty of the forecast. The direct estimation of conditional quantiles of wind power output has been achieved using hybrid deep-learning models extended to probabilistic models using the integration of the quantile regression and the deep learning models.

The models produce prediction intervals that are used to measure the range of possible future power values at a particular confidence level. Hybrid models with deep-learning and probabilistic loss functions can represent uncertainty distributions and central tendencies in wind power predictions. This will be of immediate benefit to risk-sensitive operations of power systems and their market bidding policies, which are defined by deterministic and probabilistic models of wind power forecasting, respectively, as shown in Figure 5 with their added benefit of uncertainty estimation.

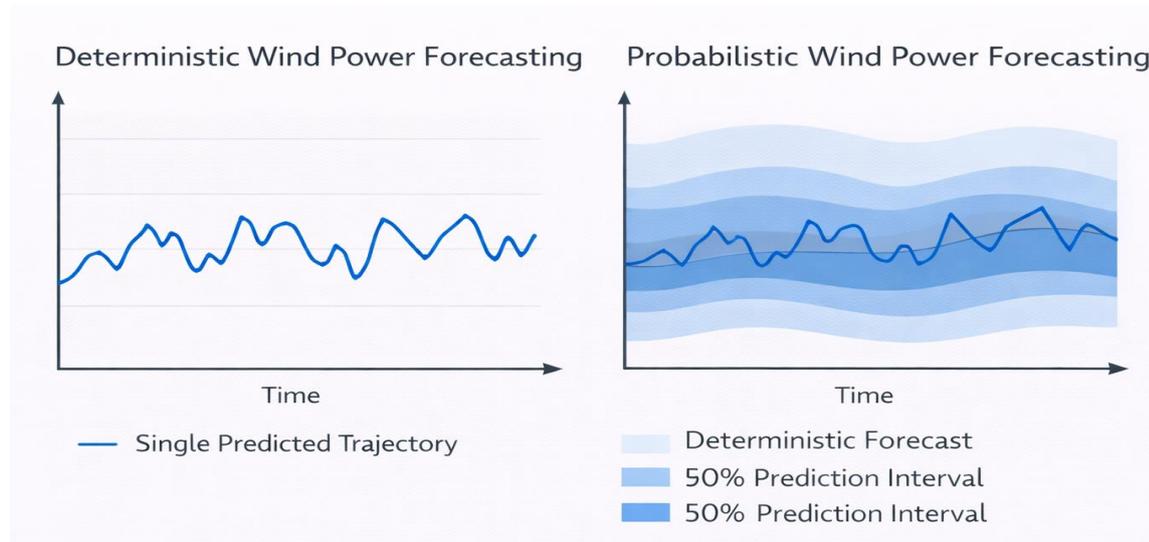


Figure 5: Deterministic vs. Probabilistic Wind Power Forecasting

### Spatial Wind Forecasting

Spatial wind forecasting aims to predict wind power output across multiple geographically distributed sites simultaneously. This task is challenging due to spatial correlations, terrain effects, and varying atmospheric conditions across locations. Hybrid deep-learning models have been effectively applied to address these challenges through multi-site forecasting frameworks.

CNN and LSTM combinations are particularly well-suited for spatial wind forecasting. In such models, CNN layers extract spatial features from gridded wind data or multi-site measurements, capturing correlations between neighboring locations. LSTM layers then model the temporal evolution of these spatial features, enabling accurate forecasting across multiple wind farms. This hybrid structure improves forecasting consistency and reduces error propagation in interconnected wind power systems.

### Hybrid Models for Solar Power Forecasting and Comparative Discussion

Hybrid deep-learning models have been extensively applied to solar power forecasting to address the strong variability and uncertainty introduced by atmospheric conditions, particularly cloud dynamics. Compared to wind power forecasting, solar forecasting places greater emphasis on irradiance modeling, image-based inputs, and rapid fluctuation capture. This section discusses hybrid models for solar forecasting and provides a comparative analysis with wind forecasting approaches.

### Solar Irradiance vs Power Forecasting

Solar forecasting can be broadly categorized into solar irradiance forecasting and photovoltaic power forecasting, each requiring distinct modeling strategies. Irradiance forecasting focuses

on predicting incoming solar radiation, which is directly influenced by cloud cover, aerosols, and atmospheric conditions. These models often rely heavily on meteorological variables and sky or satellite imagery.

In contrast, power forecasting incorporates the nonlinear conversion of irradiance into electrical output, accounting for system-specific factors such as panel orientation, temperature effects, inverter efficiency, and shading. Hybrid deep-learning models are particularly effective in this context, as they can integrate physical relationships with data-driven learning to capture both environmental variability and system behavior.

### Image-Based Hybrid Forecasting

Image-based forecasting has become a key area of solar power prediction due to its ability to capture cloud movement and spatial irradiance variability. Hybrid deep-learning frameworks have been developed to process visual data alongside numerical inputs.

In sky image-based forecasting, convolutional neural networks are used to extract spatial features from ground-based sky images, such as cloud texture, coverage, and motion patterns [25]. These features are then combined with temporal models to predict short-term changes in solar irradiance and power output. Spatial wind forecasting is done to predict the power output of the wind in more than one geographically spread location at once. This is not an easy task because spaces are correlated, terrain is also affected, and different locations have different atmospheric conditions. Multi-site forecasting frameworks have been utilized to deal with these problems by using hybrid deep-learning models.

CNN in combination with LSTM is especially suitable for predicting spatial winds. CNN layers in these models compute features of the spatial gridded wind data or measurements at multiple sites, and identify correlations among neighboring points. These spatial features are then modelled over time by LSTM layers so that the time development of the multiple wind farms can be accurately predicted. Such a hybrid form of structure enhances consistency of the forecast and delays the error propagation in the interdependent wind power systems.

Equally, the satellite data-based forecasting makes use of the series of satellite images as a source of capturing large scale cloud movement. CNNs, used to extract spatial features, are used in hybrid architectures, whereas the LSTM network predicts the time dynamics of cloud patterns. This combination allows better short term and intra hour forecasting. An example hybrid model of predicting solar by means of sky imaging by CNN and LSTM is shown in Figure 6.

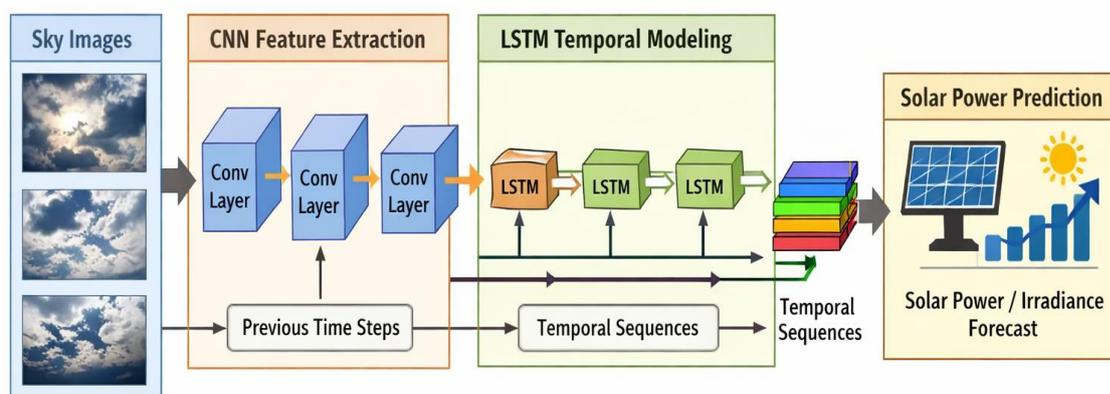


Figure 6: Hybrid CNN–LSTM Framework for Sky Image–Based Solar Power Forecasting

## Hybrid Models for PV Output Forecasting

In addition to image-based techniques, a wide range of applications of hybrid deep-learning models are found in photovoltaic output prediction based on numerical time-series data. Wavelet-LSTM networks separate irradiance or power signals into various frequency responses, and allow the LSTM network model rapid change as well as longer-term tendencies in a more effective way[26].

The other interesting method is ANFIS-CNN hybrid models, a situation where fuzzy logic systems are used to manage uncertainties and nonlinear relations whereas cnn models are applied to elicit salient features in input data. Table 6 provides a comparative summary of representative types of hybrid models applied in solar predictions emphasizing their main peculiarities and the situations of their application.

**Table 6: Comparison of Hybrid Models For Solar Forecasting**

Hybrid Model	Input Data	Key Strength	Application
Wavelet-LSTM	Irradiance, power time series	Noise reduction and temporal modeling	PV power forecasting
CNN-LSTM	Sky images, meteorological data	Spatial-temporal feature extraction	Short-term solar forecasting
ANFIS-CNN	Meteorological variables	Uncertainty handling and interpretability	PV output forecasting
Satellite-CNN-LSTM	Satellite images	Large-scale cloud motion modeling	Regional solar forecasting

## Deterministic vs Hybrid Forecasting Performance

The type of hybrid deep-learning models typically beats the traditional deterministic forecasting methods because of the use of complementary modeling strategies. The combination of decomposition methods, feature extraction and temporal learning would result in a lot of increase in accuracy especially in quickly changing weather conditions.

Besides the better accuracy, contrary to isolated high-order models, hybrid ones are more robust, that is, less sensitive to noise and input uncertainty. Its strength is particularly significant in solar forecasting, where an abrupt change of clouds may lead to severe power swings that are hard to detect with the single-model method.

## Wind vs Solar Hybrid Model Behavior

Although hybrid deep-learning models have been shown to perform quite well in predicting wind and solar energy, there is a difference in their behavior; this is attributed to the natures of the particular resources. The wind forecast models tend to be more turbulent and spatially varied whereas the solar forecast models are very sensitive to cloud dynamics and variations of irradiance.

The wind forecasting hybrid models tend to focus on the signal decomposition and temporal learning shortcuts whereas solar forecasting models tend to focus on the spatial features extraction and image-based input. These variations point to the necessity of resource-specific hybridization techniques that would be applicable to the predominant sources of uncertainty.

## Computational Complexity and Practical Deployment

Although hybrid deep-learning models have better performance, they also add extra computational complexity in the form of multi-stage processing, decomposition or optimization stages. Such models often need huge computational resources and huge datasets to be trained.

Practically in terms of deployment real time viability is based on model complexity, availability of data, and on computational infrastructure. Although it can be noted that hybrid models can be effectively used in an operational setting, Table 7 contains a summary of their strengths and limitations, and there is always a need to design the model carefully and simplify to strike the right balance between the quality of the forecast and the computational efficiency.

**Table 7: Strengths and Limitations of Major Hybrid Deep-Learning Approaches**

Hybrid Approach	Strengths	Limitations
Decomposition + DL	High accuracy, noise reduction	Increased preprocessing complexity
CNN-LSTM	Strong spatial-temporal modeling	High computational cost
ANFIS-DL	Uncertainty handling, interpretability	Rule design complexity
Optimization-based DL	Improved convergence and accuracy	Additional optimization overhead

## Open Challenges, Research Gaps and Future Research Directions

Although hybrid deep-learning models are proven to be efficient in the field of wind and solar energy prediction, a number of research gaps and open challenges exist that have not yet permitted their widespread applications and operational consequences. Among the most important issues is the problem with quality and availability of data since the forecast of performance is very sensitive to the quality and completeness of input information. The data that is missing or ineffective sensors, as well as the lack of communication in the measurement systems can greatly diminish the reliability of the model especially in the data-driven hybrid methods, which rely on extensive historical data sets. Data preprocessing, imputation and fault tolerant model designs are thus very critical but not adequately discussed.

Generalization and transferability is another important challenge. Most hybrid forecasting models have been constructed and tested on a site, type of turbine or photovoltaic installation leading to good performance site-specifically but poor performance in new locations. The absence of broad cross-regional validation necessitates the perception of model strength across varying climatic and geographical settings, and there is urgency to have transferable modeling models and comparable evaluable practices.

Another research gap is also the interpretability of hybrid deep-learning models. The accuracy of the prediction may be enhanced by the hybridization, though it usually enhances the complexity of the model, contributing to the fact that the systems of deep-learning are black-box. There has been a small number of attempts to explain behavior of models or quantify the contribution of individual inputs and components limiting trust and acceptance of system

operators. Initial explainability methods have provided a starting point but merit development to assist with the transparent and interpretable forecasting solutions.

Moreover, the hybrid forecasting models are not fully integrated into the power system processes. Although numerous studies have shown enhanced accuracy when using offline assessments, few studies have been conducted to encourage real world implementations including the computational limitations, latency of the data and its occurrence with the existing energy management systems. This discontinuity highlights the necessity to have those forecasting models that are both technically efficient and practically viable.

## CONCLUSION AND RECOMMENDATIONS

### Conclusion

Exact prediction of the wind and solar energy production is an essential factor to the efficient and cost-effective work of the contemporary power systems where high rates of renewables are involved. This review has provided a somewhat thorough discussion of hybrid deep-learning models that have been created to solve the specific problems related to the forecasting of renewable energy, such as intermittency, nonlinearity, uncertainty, and spatial-temporal variability. A combination of deep-learning models with other related methods including signal decomposition, machine learning, fuzzy inference, and optimization algorithms has proven to be more advantageous to a hybrid type of model than the conventional approaches and standalone methods.

In a systematic review, the hybrid forecasting models were categorized based on the structural design and the integration strategies they employ with the strengths and limitations of each category noted. The hybrids of decomposition based were mentioned to be very useful in minimizing the noise and also generalizing the temporal learning and the machine learning deep learning hybrids developed feature representation and generalization. Fuzzy and neuro-fuzzy hybrids added interpretability and uncertainty management and optimization-based hybrids improved model convergence and performance. The applications of wind and solar forecasting described have shown the adaptation of hybrid models to the features of resources, prediction horizons and the needs of operations.

Regardless of these achievements, a number of obstacles still exist that can restrict the further application of hybrid deep-learning models on actual operation of power systems. The problem of data quality, generalization of models, interpretability and the complexity of the computation still presents a setback to deployment. To cope with these challenges, concerted efforts should be made to develop common standards of evaluation practices, enhanced explainability, and enhanced integration with the process of operational decision making.

On the whole, hybrid deep-learning models are a current and efficient category of prognostic devices that can fill the gap between strictly data-driven forecasting tools and realistic requirements of the power system. Future studies in the field are likely to improve the accuracy of forecasting, the strength, and convenience to a greater extent, enabling the effective world of the wind and solar energy into future power systems. The review demonstrates that hybrid deep-learning models can significantly enhance the accuracy and reliability of renewable energy forecasting, thereby supporting more informed operational decision-making. These models improve grid stability and enable effective ramp-rate control, reducing the risks associated with sudden fluctuations in renewable generation. From an economic perspective, they help minimize imbalance costs and facilitate more strategic participation in energy markets. In addition, the study highlights areas for research advancement by identifying gaps related to model generalization, interpretability, and uncertainty quantification. Finally, the

insights gained from these hybrid approaches can inform policy and planning, supporting renewable capacity expansion and more efficient energy management practices.

### **Recommendations**

Considering a prospective viewpoint in the field, it is possible to single out a number of promising research directions. The future collaboration is anticipated to consider better approaches of hybridization that are more successful to integrate decomposition, learning and optimization methods with the aim of decreasing the computational burden. It is expected that the construction of probabilistic and ensemble hybrid models will further quantify uncertainty on risks and decision-making via risk-aware decision-making. Greater interaction with the numerical weather prediction data provides new chances to satisfy the exploitation of meteorological data within the various horizons of forecasting. Also, the concept of edge computing offers a possible avenue towards the deployment of lightweight hybrid models, which bring access to speedier responses and enhanced scaling, despite the fact that these approaches are conceptual in this respect. Although hybrid deep-learning models show improved accuracy, they face challenges including poor generalization to new locations, limited interpretability, high computational cost, and insufficient integration with operational grid management. These gaps guide the study in assessing the effectiveness and applicability of hybrid models across wind and solar forecasting scenarios.

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