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Artificial Intelligence for Forecasting Solar, Hydropower, and Wind Renewable-Energy Systems: A Comparative Analysis

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ABSTRACT

The increasing integration of renewable energy sources into modern power systems has created a strong demand for accurate and reliable forecasting methods. Solar, wind, and hydropower systems are highly dependent on meteorological and hydrological conditions; therefore, accurate forecasting is essential for grid stability, optimal energy scheduling, and operational efficiency. Artificial intelligence (AI) has emerged as a powerful and widely adopted approach for renewable energy forecasting due to its ability to model complex nonlinear relationships and extract patterns from large-scale datasets. In solar energy forecasting, multilayer perceptron (MLP) and long short-term memory (LSTM) models are commonly used to predict power generation using historical and meteorological data. Wind energy forecasting commonly employs artificial neural networks (ANNs), support vector regression (SVR), and Gaussian process regression (GPR) to model nonlinear wind behavior and quantify prediction uncertainty. Hydropower forecasting utilizes support vector regression (SVR) and hybrid models, such as Gaussian process regression combined with the cooperation

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search algorithm (GPR–CSA), to estimate hydrological variables and predict power output. This review compares these approaches in terms of predictive accuracy, robustness, computational efficiency, data requirements, and their ability to handle resource-specific uncertainty.

GRAPHICAL ABSTRACT

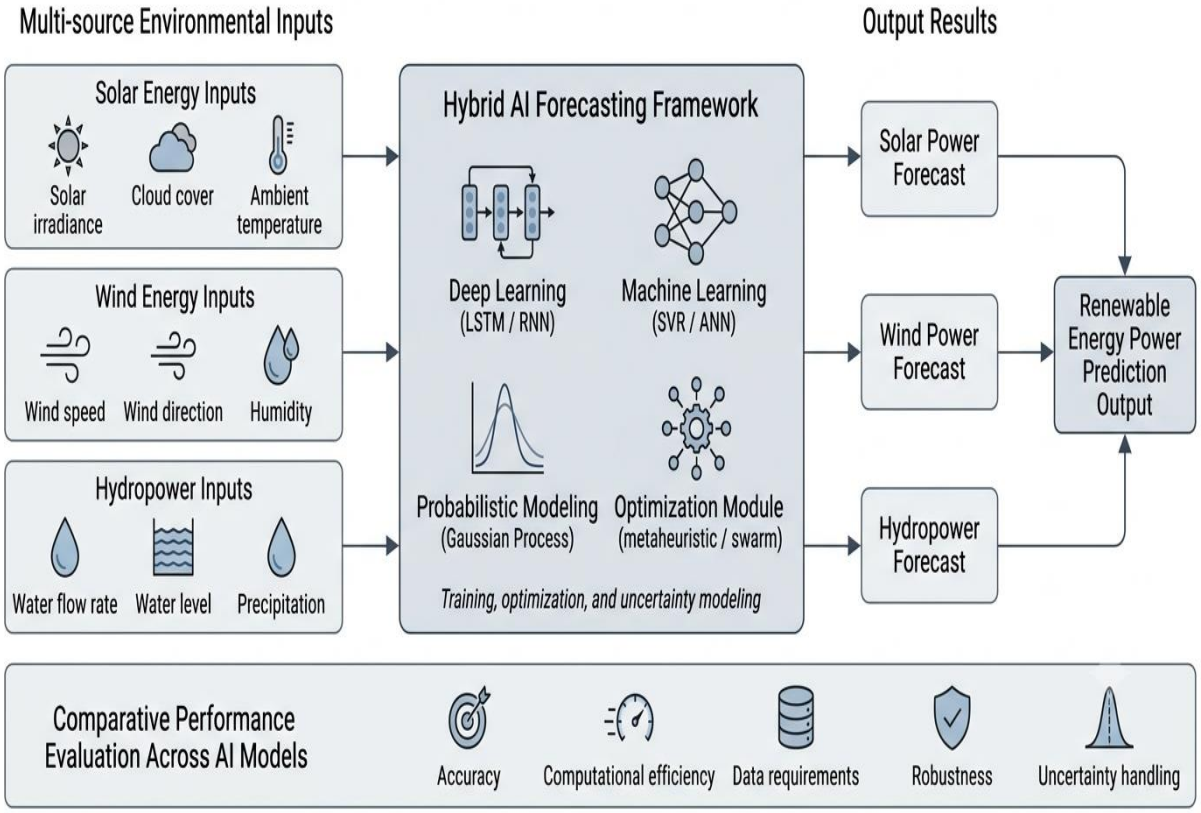

Figure 1. Conceptual illustration of AI techniques in renewable-energy system

INTRODUCTION

Role of AI in RESs

Artificial intelligence (AI), often described as machine-based intelligence, is central to advanced automation and data-driven decision-making [1]. The global transition to sustainable energy has increased the need for AI-based approaches that improve reliability, and economic performance [2]. Advances in machine learning have strengthened the clean-energy sector and can support a more sustainable [3]. AI techniques are used throughout renewable-energy systems, including generation forecasting, predictive maintenance, power optimization [4], energy storage [5], grid integration [6] power-network management [7], and decentralized renewable-energy networks [8]. In renewable-energy forecasting, AI has become an important tool for improving the accuracy of projected energy generation and operational optimization [9]. Forecasting is the process of estimating a future outcome [10], and accurate

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prediction is essential for reliable renewable-power generation [11]. Recent advances combine AI techniques with renewable-energy infrastructure, transmission networks, and exchange [12]. For example, machine-learning algorithms can predict cloud cover and rapidly changing weather conditions for photovoltaic systems, as well as wind speed and direction for wind turbines [2]. A power system that relies entirely on renewable resources requires substantial changes in grid design and operation [13]. Integrating AI with renewable-energy infrastructure has helped transform conventional electricity networks into intelligent energy systems with improved operational performance [14], advanced control [15], bidirectional data exchange [16]

Problem statement

The increasing penetration of renewable energy sources (RESs), such as solar, wind, and hydropower, has introduced significant uncertainty and variability into modern power systems. Accurate forecasting of renewable energy generation is essential for ensuring grid stability, optimizing energy management, and supporting sustainable energy transitions. Traditional statistical and physical forecasting methods often struggle to capture the nonlinear, stochastic, and complex behavior of renewable energy resources, resulting in limited prediction accuracy under varying environmental conditions. Recent advances in artificial intelligence (AI), including machine learning, deep learning, and hybrid intelligent models, have demonstrated considerable potential for improving forecasting performance. Therefore, a comprehensive review is needed to systematically analyze and synthesize existing AI-driven forecasting approaches for renewable energy sources. Such a review aims to identify current trends, evaluate model performance, highlight research gaps, and provide insights into future directions for developing more accurate, robust, and interpretable forecasting frameworks for sustainable energy systems.

Research gaps in AI based RESs

AI forecasting models require large, accurate, standardized, and harmonized datasets; however, renewable-energy data are often incomplete, inaccurate, or heterogeneous [17]. AI algorithms still struggle to forecast highly dynamic and variable resources, particularly wind and solar energy [18]. Limited or low-resolution data reduce the effectiveness of feature-extraction methods [18]. Many AI forecasting models, particularly deep-learning models, lack transparency, which can make operational decisions difficult to interpret. AI models may perform well in simulations but deteriorate under real-grid conditions, including sensor failures and communication disruption [19]. No universal forecasting model performs equally well across short-, medium-, and long-term prediction horizons [20]. Most AI and deep learning models used for solar and wind forecasting operate as black boxes. Although they provide high accuracy, they lack interpretability, robustness assessment, and trustworthiness, which limits their deployment in real-world power systems [21]. Many forecasting models are trained and validated using site-specific datasets. Their performance degrades when applied to different geographical regions, climates, or newly installed renewable plants. Cross-regional validation and transfer learning remain underexplored [22]. Current AI forecasting studies primarily focus on point prediction accuracy while neglecting

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uncertainty quantification, model drift, retraining strategies, and real-time deployment constraints. Consequently, many models remain difficult to integrate into operational smart grids [23], [24].

Objectives of using AI in RESs

The paper investigates the role of computational intelligence in renewable-energy generation and the transition to sustainable power. It examines how AI algorithms can improve renewable-energy output and forecasting accuracy. These models use historical observations and meteorological variables to predict solar and wind generation, estimate grid capacity, support system management, and plan future operating cycles. The report compares AI-based models for solar, wind, and hydropower forecasting in terms of accuracy, forecast horizon, data dependence, feature sensitivity, computational complexity, scalability, robustness, and the effectiveness of hybrid approaches the study also provides an overview of AI tools suited to individual renewable resources and explains the mechanisms through which these models transform raw environmental and operational data into useful energy forecasts. Its central aim is to present a clear comparative assessment of AI-based forecasting methods and their contribution to reliable renewable-energy operation.

Fundamentals of Renewable Energy system

Solar Energy

Solar energy is one of the most promising renewable energy resources because it converts abundant solar radiation into useful electrical and thermal energy with minimal environmental impact. The working principle of photovoltaic (PV) systems is based on the photovoltaic effect, in which semiconductor p–n junctions absorb incident photons and generate electron–hole pairs that produce direct current electricity. Solar thermal systems, in contrast, convert solar radiation into heat through collectors and utilize this thermal energy for water heating, space heating, industrial processes, or electricity generation through concentrated solar power technologies. PV technologies are generally classified into first-generation crystalline silicon cells (monocrystalline and polycrystalline), second-generation thin-film technologies such as amorphous silicon (a-Si), CdTe and CIGS, and third-generation emerging technologies including perovskite, dye-sensitized, organic, and tandem solar cells, while solar thermal technologies comprise flat-plate collectors, evacuated tube collectors, parabolic trough collectors, solar towers, dish collectors, and hybrid photovoltaic-thermal (PV/T) systems. Solar energy offers numerous advantages, including inexhaustible availability, zero greenhouse gas emissions during operation, low maintenance requirements, modularity, suitability for distributed generation, energy security enhancement, and continuously declining installation costs. Hybrid PV/T systems further improve overall energy utilization by simultaneously producing electricity and heat. However, several limitations hinder widespread deployment, including intermittency caused by weather and diurnal cycles, reduced PV efficiency at elevated temperatures, dependence on energy storage and grid support, high initial investment costs, land requirements for utility-scale installations, degradation of modules over time, recycling and disposal challenges, and the relatively complex and costly infrastructure associated with concentrated solar thermal technologies. Despite these challenges, ongoing

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advancements in materials, cooling techniques, energy storage, and intelligent control systems are continuously improving the efficiency, reliability, and economic viability of solar technologies, reinforcing their crucial role in achieving sustainable and low-carbon energy systems worldwide [25-33].

Wind energy

Wind energy is a clean, renewable, and rapidly expanding source of electricity that converts the kinetic energy of moving air into electrical power using wind turbines. Wind is produced by the uneven heating of the Earth's surface by the sun, creating pressure differences that cause air to move. Modern wind turbines capture this energy through aerodynamic blades connected to a generator, producing electricity without direct greenhouse gas emissions. Wind turbines are mainly classified into **Horizontal Axis Wind Turbines (HAWTs)** and **Vertical Axis Wind Turbines (VAWTs)**. HAWTs dominate the global market because of their higher efficiency, larger power output, and suitability for utility-scale wind farms, although they require yaw systems to face the wind. In contrast, VAWTs can accept wind from any direction, operate well in turbulent environments, and have easier maintenance due to ground-level equipment, but their lower efficiency has limited large-scale commercialization. Wind farms are further categorized as **onshore** and **offshore** systems. Onshore wind farms are more common because they are less expensive to install, easier to maintain, and supported by existing infrastructure. Offshore wind farms, located in coastal and deep-sea regions, experience stronger and more consistent winds, resulting in higher energy production despite greater installation and maintenance costs. Recent developments in larger turbines, floating offshore wind technology, advanced composite materials, digital monitoring, and artificial intelligence have significantly improved the efficiency, reliability, and economic competitiveness of wind energy. Consequently, wind power has become one of the most important renewable energy technologies for reducing greenhouse gas emissions, improving energy security, and supporting the global transition toward a sustainable low-carbon energy system [34-39].

Hydropower

Hydropower is one of the oldest, most reliable, and widely used renewable energy technologies, generating electricity by converting the potential and kinetic energy of flowing or falling water into mechanical energy through hydraulic turbines connected to generators. Hydropower plants are generally classified into reservoir (storage**)**, run-of-river, pumped storage, and micro-hydro systems. Reservoir hydropower stores water behind a dam, allowing controlled electricity generation, flood control, irrigation, and water supply, although it may have significant environmental and social impacts. Run-of-river plants generate electricity using the natural flow of rivers with little or no water storage, reducing environmental impacts but producing variable power depending on river discharge. Pumped storage hydropower (PSH) functions as a large-scale energy storage technology by pumping water to an upper reservoir during periods of low electricity demand and releasing it to generate electricity during peak demand, thereby supporting grid stability and the integration of intermittent renewable sources such as wind and solar energy. Micro-hydro systems, typically with capacities below 100 kW, provide decentralized, reliable, and cost-effective electricity for rural and remote

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communities with minimal environmental disturbance. Continuous advancements in turbine design, digital control systems, environmental flow management, and smart grid integration have improved the efficiency, flexibility, and sustainability of hydropower, making it a vital component of global renewable energy systems and the transition toward low-carbon electricity generation [40-46].

1.2. Comparison

Solar, wind, and hydropower are the three most widely used renewable energy technologies, each offering unique advantages in terms of efficiency, installation cost, environmental impact, and reliability. Hydropower is the most efficient, with energy conversion efficiencies of 85–95%, and provides reliable, dispatchable electricity with operational lifetimes often exceeding 50 years. However, it requires high initial investment, long construction periods, and may cause ecological impacts such as habitat alteration, river fragmentation, and changes in aquatic ecosystems. Wind energy achieves conversion efficiencies of approximately 35–50%, has moderate installation costs, and produces very low greenhouse gas emissions during operation. Although wind power is cost-effective and suitable for large-scale electricity generation, its intermittent nature requires grid support or energy storage, and wind farms may affect birds, bats, and landscape aesthetics. Solar photovoltaic (PV) technology has commercial module efficiencies of approximately 20–25% and has experienced the fastest decline in installation costs due to technological advancements and mass production. Solar energy is highly modular, easy to install, and generates electricity without operational emissions, making it suitable for residential, commercial, and utility-scale applications. However, its performance depends on sunlight availability and often requires battery storage to ensure reliable power supply during nighttime or cloudy conditions. Overall, hydropower remains the most efficient and reliable renewable energy source, wind energy provides an excellent balance between performance and cost, while solar PV offers the greatest flexibility and scalability. Therefore, integrating solar, wind, hydropower, and energy storage into hybrid renewable energy systems is widely recognized as the most effective strategy for improving energy reliability, minimizing environmental impacts, and supporting the global transition toward a sustainable low-carbon energy future [47-53]. Thus, renewable-energy forecasting is essential because resources such as solar and wind are intermittent and weather-dependent, creating challenges for grid stability and energy planning. Accurate forecasts support generation scheduling, economic dispatch, reserve estimation, and system reliability. Forecasting also facilitates the integration of renewable energy into power systems by improving the balance between electricity supply and demand [54]

Classical forecasting models for renewable-energy systems

Classical forecasting methods form the foundation of renewable-resource prediction by using statistical relationships, physical principles, and historical data patterns to [55] future energy availability [72]. Common approaches include persistence methods, autoregressive and time-series models, and regression-based frameworks that relate renewable-energy output to meteorological variables such as wind speed, solar irradiance, and temperature. These methods remain widely used because they are

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interpretable, computationally efficient, and effective over short to medium horizons. They also provide essential baselines for evaluating modern forecasting approaches. Classical methods can capture temporal variability and seasonal trends, thereby supporting grid operation, energy scheduling, and reliability planning [56, 57]

Persistence method

Persistence is one of the simplest classical approaches to renewable-energy forecasting, particularly for very-short-term wind and solar prediction. It assumes that future resource conditions will remain similar to the most recent observation. Despite its simplicity, persistence is widely used as a baseline for evaluating advanced methods. It can provide reasonable accuracy under stable atmospheric conditions and remains an important benchmark in renewable-energy forecasting [58-61].

Time-series (ARIMA-based) method

The autoregressive integrated moving-average (ARIMA) model combines autoregressive and moving-average components after differencing the time series to improve stationarity. It forecasts future observations from patterns and errors in historical records. ARIMA-based methods model the relationship between an outcome and its previous values, while accounting [62] stochastic disturbances and time-varying patterns [78]. These approaches rely primarily on historical observations and are valued for their mathematical transparency and relatively low computational requirements [63, 64]

Auto-aggressive process considers Y_t as a straight-line equation of previous data point and giving relation with self-modelling coefficient α and unpredictable disturbance ε. The Moving Average is weighted sum of present error with several past disturbances [65]

Autoregressive model:

$$Y_t = \alpha_1 Y_{t-1} + \varepsilon_t$$

Integrated process:

$$Y_t = Y_{t-1} + \varepsilon_t$$

Moving-average model:

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1}$$

Regression-based statistical method

Regression analysis examines numerical data to estimate model coefficients and generate predictions. In renewable-energy [66] forecasting, regression methods establish relationships between power output and meteorological variables such as temperature, wind speed, solar irradiance, and atmospheric pressure [67]. These frameworks provided an important foundation for renewable-energy forecasting before the widespread adoption of machine-learning techniques [68]

Challenges of classical forecasting methods

Classical ARIMA models showed low predictive performance with negative R^2 in renewable forecasting experiments [69]. ARIMA has produced substantially higher forecast errors than neural-network models in several comparisons, indicating limited

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ability to represent complex nonlinear behavior [70]. The volatility and uncertainty of wind and solar generation create operational challenges that classical statistical methods may not fully capture [71]. Traditional forecasting methods often deteriorate when renewable-energy datasets contain noise, irregular observations, or rapidly changing patterns [72]. Artificial intelligence is increasingly necessary for forecasting renewable-energy systems because resources such as wind and solar are intermittent, stochastic, and [73] highly variable, making them difficult to predict with conventional approaches [20,90]. Accurate AI-enabled forecasts support efficient scheduling, energy management, [74] and grid stability under uncertain conditions [91]. Consequently, AI-driven forecasting is increasingly recognized as an important tool for improving the efficiency, reliability, and economic operation of modern renewable-energy systems [72], [75]

Artificial Intelligence Overview

Artificial intelligence combines computational methods with capabilities [76] as learning, reasoning, and decision-making [92,93]. AI methods are particularly useful when the relationship between inputs and outcomes is [77] uncertain, or difficult to express analytically. By integrating data, domain knowledge, and uncertainty analysis, these algorithms can evaluate complex associations between causal factors and predicted outcomes. Unlike many manual analytical methods, AI can process large volumes of qualitative and quantitative data efficiently [78].

History of AI development in renewable-energy forecasting

Before machine-learning methods were introduced in the early [60], renewable-energy [79] forecasts relied primarily on physical and [80] approaches, including persistence models [17], time-series models [18], and numerical weather-prediction models [73]

Table 1. Historical evolution of artificial intelligence in renewable-energy forecasting

Stage	Models	Forecasting applications	Reference
Early stage (1990–2000)	Artificial neural networks, knowledge-based systems, and decision-support systems	Power-demand optimization, fault identification, and optimal power-flow improvement.	[17]
Development stage (2000–2010)	Perceptron-based neural networks, kernel-based learning models, and temporal forecasting models	Forecasting applications Forecasts of electricity-network reliability, solar irradiance, wind speed, and wind magnitude,	[81]

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		supported by the expansion of solar and wind power plants.	
Expansion stage (2010–2019)	GEFCom encouraged the development of hierarchical learning and temporal neural networks.	Large-scale predictive data processing and integration with next-generation power systems.	[82, 83]
Current stage (2020–present)	Deep neural networks, remote-sensing imagery, IoT-enabled sensors, and on-demand cloud computing	Near-real-time load and demand forecasting, optimal energy storage, advanced grid control, and improved solar-power production.	[84, 85]

Models used for AI-based forecasting of renewable-energy systems

Machine learning

Machine learning comprises computational methods that learn patterns from data and adapt to real-world conditions. These methods form the foundation of modern data analytics [27]. Machine-learning models [86] trained using raw or processed observations and generally follow two phases: model training and model testing or validation [28,29]. During training, an algorithm learns relationships from historical data; during [87] testing, its predictive performance is evaluated on unseen [87- 89].

Artificial neural networks

Artificial neural networks (ANNs) are computational models inspired by biological neural systems [31]. Common architectures [90] include feed-forward neural networks [32], [91] or feedback neural networks [92], random neural networks [93], hierarchical neural networks [94], multistage neural networks [95] and hybrid neural networks [96].

Deep learning

Deep learning is a branch of machine learning that uses multilayer neural networks to learn features and patterns automatically from large datasets [38]. Major [97] include supervised deep learning [98], self-organizing learning [94] reinforcement learning [99] and ensemble learning [100].

Reinforcement learning

Reinforcement learning is a reward-based approach in which an agent interacts with its environment, balances exploration and exploitation, and learns an optimal policy from feedback generated by previous actions [42]. Deep reinforcement learning [101] this

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process to complex problems and supports the development of autonomous systems that can interpret high-dimensional data [43]. Common algorithms include deep [102] Q-learning [44], SARSA [45], dueling [103] deep [104], [105] actor-critic learning [106].

Genetic algorithm

A genetic algorithm is a computational framework inspired by natural selection and Darwinian evolution [48]. Candidate solutions evolve through selection, [107] recombination, and mutation, allowing the method to search complex solution spaces [49]. Because of its flexibility, the approach [108] can be applied to a wide range of optimization problems [50]. Its two central components are a genetic [109] representation of the solution space and a fitness function used to evaluate candidate solutions [110].

Particle swarm optimization

Particle swarm optimization (PSO) is a nature-inspired swarm-intelligence algorithm based on the collective movement of organisms such as bird flocks. It consists of a population of particles that move through a search space to identify an optimal [111] solution [52]. Each particle updates its trajectory using its own best-known position (Pbest) and the best-known position of the swarm (Gbest) [112].

Support vector machine

A support vector machine (SVM) is a supervised-learning method that learns from data by solving a constrained optimization problem [55]. Although mathematically sophisticated and [113] computationally demanding for very large [114], SVMs can model complex classification boundaries through kernel functions [115]. The framework can also be adapted for continuous prediction as support vector regression (SVR) [116].

Random forest

Random forest, introduced in the early 2000s, is an effective general-purpose [117] classification and regression method [59]. It is an ensemble of decision trees trained on random subsets of observations [118] and features [60]. Random forests are widely used because they can handle nonlinear relationships, imbalanced datasets, missing [119] and complex feature interactions. Random sampling and model aggregation also reduce the risk of overfitting [61,62,120].

Gradient boosting

Gradient-boosting models combine optimization with sequential ensemble learning for regression, classification, and ranking tasks [121]

$$H(x) = \sum_{t} \rho_t \; h_t(x)$$

The central idea is to add estimators sequentially so that each new model is associated with the negative gradient of the loss [122] function for the existing ensemble [64].

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Extensions such as XGBoost, LightGBM, and CatBoost improve computational [123] speed and predictive performance [65]. Gradient boosting is effective because it combines multiple regression trees to solve complex optimization and prediction problems [124].

LSTM model for hydropower forecasting

The ability to retain information over long sequences is the defining feature of long short-term memory (LSTM) networks. An LSTM uses gated operations to determine which information should be retained, updated, or passed to the next time step. The forget gate removes irrelevant information, the input gate controls new information entering the cell state, and the output gate determines the information used to produce the next hidden state and forecast [125].

Forecast horizons in renewable-energy systems

Short-term forecasting

Short-term renewable-energy forecasting generally covers periods from minutes to several days and supports real-time grid operation, economic dispatch, and system stability. It relies on high-resolution meteorological inputs such as solar irradiance, temperature, and wind speed to capture resource intermittency. Machine-learning models, including LSTM, GRU, and random forest, can improve predictive accuracy by learning nonlinear temporal patterns in energy generation and demand. Short-term forecasting also supports the optimization of distributed-energy systems and efficient trading in smart [126-128].

Medium-term forecasting

Medium-term forecasting generally spans several days to several months and supports maintenance scheduling, resource allocation, and energy-market operations. It must represent seasonal variability and medium-scale weather trends affecting solar and wind output. Hybrid approaches that combine statistical methods, such as ARIMA, with deep-learning architectures, such as LSTM and CNN, can improve accuracy over these horizons. Nevertheless, uncertainty increases as weather predictions become less reliable at longer lead times [129, 130].

Long-term forecasting

Long-term forecasting extends from months to years and primarily supports strategic planning, infrastructure development, and policymaking. It considers long-term trends in demand, renewable penetration, climate, economics, and technology. Because these forecasts integrate variables such as fuel prices, climate patterns, and socioeconomic indicators, they are more complex and uncertain than short-term predictions. Hybrid and data-driven approaches can improve robustness, but long-range accuracy remains limited by the predictability of future conditions [131-132].

Standard performance metrics

Standard performance metrics are essential for evaluating the accuracy and reliability of AI-based renewable-energy forecasts. Mean absolute error (MAE) is the average

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absolute difference between predicted and observed values and provides a direct, interpretable measure of error magnitude [102, 133] mean square error (RMSE) is the square root of the mean squared prediction error and gives greater weight to large deviations, making it useful for assessing sensitivity to extreme errors [134]. Mean absolute percentage error (MAPE) expresses error as a percentage, allowing scale-independent comparisons across [133] datasets, although it can be unstable when observed values approach zero [102]. The coefficient of determination (R^2) [135] the proportion of variance explained by a model [104]. Mean bias error (MBE) identifies systematic overestimation or [136] underestimation [105], while normalized RMSE (NRMSE) facilitates comparison across datasets by scaling RMSE to a [137] reference value [106]. Symmetric mean absolute percentage error (sMAPE) uses a symmetric denominator and can be more suitable when near-zero values occur [138].

AI-based forecasting in solar-energy systems

AI-based forecasting is effective for solar-power prediction because it can represent the complex nonlinear patterns in irradiance that conventional methods may [139] capture [108]. Machine-learning and deep-learning techniques, including random forests, neural networks, and ensemble models, have achieved improved accuracy in solar-power forecasting [140]. Hybrid frameworks that combine several algorithms with time-series analysis can further improve forecast reliability and robustness [141]. Comparative studies indicate that machine-learning methods can outperform basic regression models in -short-term forecasting, helping grid operators manage variability in solar-power output [126]. Integrating domain knowledge with AI models can further improve predictions by incorporating the physical characteristics of photovoltaic systems and relevant weather variables [142].

The accuracy of solar energy forecasting largely depends on the selection of appropriate input variables that capture atmospheric and environmental conditions affecting photovoltaic (PV) power generation. Among these, solar irradiance is the most influential predictor because it directly determines the amount of solar energy reaching PV modules and exhibits the strongest correlation with power output. Ambient temperature affects PV cell efficiency, as higher temperatures generally reduce electrical conversion efficiency. Relative humidity influences atmospheric transparency by increasing water vapor content, which scatters and absorbs incoming solar radiation. Cloud cover is another critical variable because it causes rapid fluctuations in solar irradiance through cloud movement and shading, making it essential for short-term forecasting. Wind speed indirectly improves PV performance by cooling solar panels, thereby reducing module temperature and increasing conversion efficiency. In addition, aerosol concentration (commonly represented by aerosol optical depth, AOD) modifies the attenuation of solar radiation through scattering and absorption, particularly in regions affected by dust or pollution. Recent advances in artificial intelligence have further incorporated satellite images, which provide large-scale cloud distribution and cloud motion information for forecasting from several minutes to hours ahead, while ground-based sky images offer high spatial and temporal resolution for detecting local cloud dynamics, significantly enhancing very short-term (nowcasting) solar irradiance predictions. Consequently, integrating

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meteorological variables with satellite and sky-image data enables machine learning and deep learning models to capture both temporal and spatial variations in atmospheric conditions, resulting in more accurate and reliable solar power forecasting [68, 143, 147].

Multilayer perceptron

The multilayer perceptron (MLP) is a widely used neural-network model capable of representing complex nonlinear relationships in solar-power forecasting. It consists of an input layer, one or more hidden layers, and an output layer. Each neuron combines weighted inputs and a bias term before applying an activation function. Training uses forward propagation to generate predictions and backpropagation to minimize the difference between predicted and observed values. Regularization and [148, 149] methods can improve generalization and reduce overfitting [112,113]. Inputs may include ambient temperature, atmospheric pressure, clearness index, wind speed and direction, cloud cover, sunshine duration, and relative humidity, together with historical irradiance observations.

Mathematically, the model can be represented as follows:

$$(G_i) = \tilde{f}(T_t, S_t, RH_t, Ws_t, Wd_t, Kt_t, Cl_t, P_t, Lat, Lon)$$

$$(G_{i+p}) = \tilde{f}\left(G_{i+p-1}, G_{i+p-2}, \ldots., G_i\right)$$

The task involves identifying a functional relationship between input and output data that enables the prediction of future values at time $t + p$, using previously observed data from earlier time steps $(t + p - 1, t + p - 2, \ldots, t)$. After merging the first two mathematical equations,

$$(G_{i+p}) = \check{f}\left(G_{i+p-1}\, G_{i+p-2}, \ldots, G_i, T_t, RH_t, S_t, Ws_t, Wd_t, K_t, Cl_t, p_t, L_{at}, L_{on}\right)$$

These above functions are integrated for final results. All the variables and solar intensity data are measured at temporal time progression $(t + p - 1, t + p - 2, \ldots, t)$ for satisfactory neural network model results for prediction [150], [151].

Mathematically, the hidden layer output is expressed as $h_j = f(\sum_{i=1}^{N} w_{ij}\, x_i + b_j)$, and the final output is given by $y_k = f(\sum_{j=1}^{M} v_{jk}\, h_j + c_k)$, forming a nested nonlinear mapping between inputs and predicted solar values. The model is trained using supervised learning, where the error between predicted and actual values is minimized using a loss function $E = \frac{1}{2}\sum_k (y_k - t_k)^2$, and weights are updated through backpropagation using gradient descent or advanced optimization algorithms such as Levenberg–Marquardt. The gradient computation follows the chain rule, enabling efficient propagation of error from output to input layers. In solar forecasting applications, MLP models typically use inputs such as temperature, humidity, wind speed, and historical irradiance data, and have demonstrated strong performance in short-term forecasting tasks due to their flexibility and nonlinear approximation capability [152-155].

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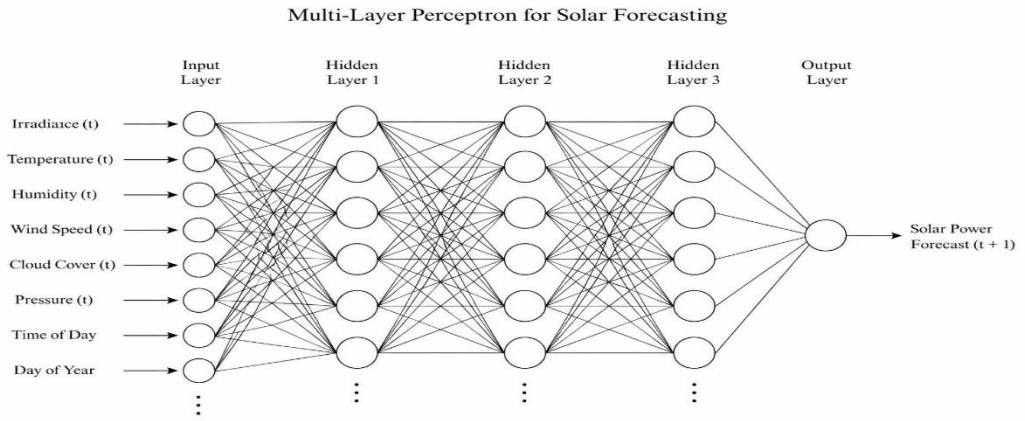

Figure 2. Illustration of multi-layer perceptron in prediction of solar energy system

LSTM for solar forecasting

LSTM networks are widely used in solar-energy forecasting because they learn temporal patterns in sequential meteorological data. They are well suited to photovoltaic prediction because solar generation depends on historical irradiance and changing weather conditions. Compared with conventional neural networks, LSTM models can represent long-term dependencies while reducing vanishing-gradient problems. Historical irradiance, temperature, and other weather variables are supplied as sequential inputs, [68, 148, 156-158] and gates retain relevant information and discard irrelevant data. This enables the model to learn both short-term fluctuations and longer-term trends in solar-power generation [159].

Table 2. Mathematical expressions describing LSTM operation

Gated mechanism	Equation	References
Forget gate The forget gate determines how much previous information is retained	$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$	[160]
Input gate The input gate controls how much new information is added to memory	$i_t = \sigma(W_i x_i + U_i h_{t-1} + b_i)$	[161]
Cell state update The cell state is updated using both previous and newly generated information	$\tilde{C}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$ $C_t = f_t . C_{t-1} + i_t . \tilde{C}_t$	[162]
Output gate	$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$	[161]

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The output gate controls how much internal memory contributes to the model output

Hidden state

The hidden state represents the learned temporal features used for prediction

$$h_t = o_t \cdot \tanh(C_t) \quad [161]$$

Forecasting equation

The forecasting layer maps the hidden state to the predicted solar output

$$\hat{P}(t) = W_y h_t + b_y \quad [148]$$

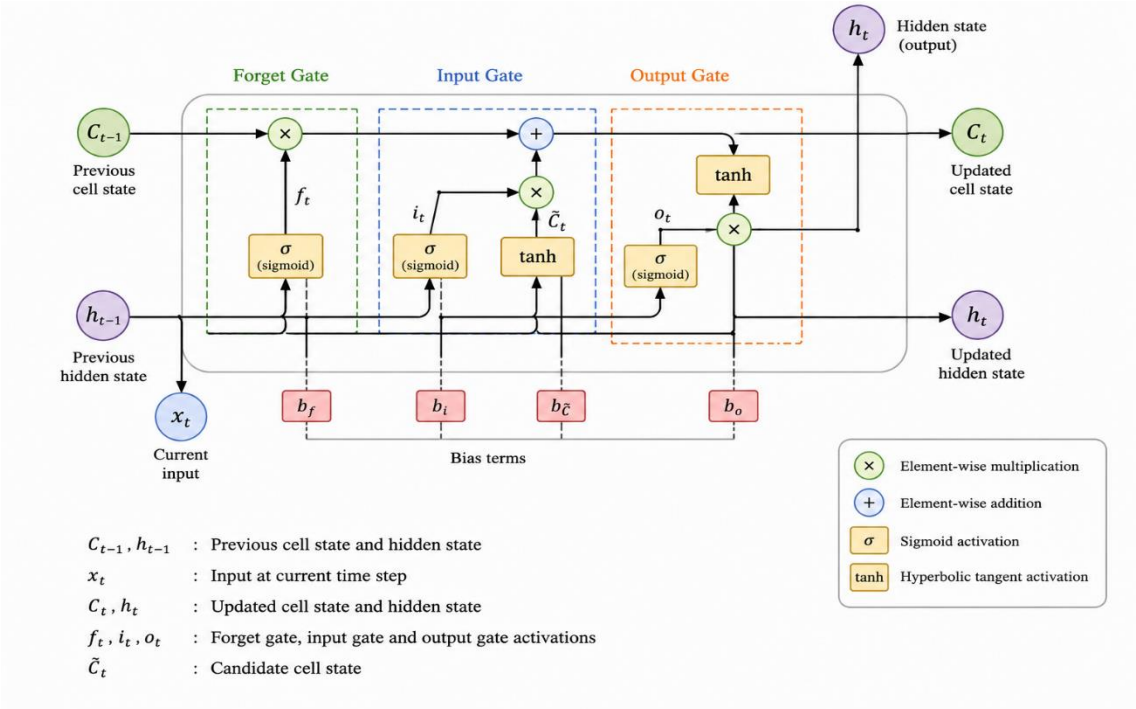

Figure 3. LSTM architecture for solar-energy forecasting

Table 3. Standard performance metrics used in AI-based solar-energy forecasting

Metrics	Definition	Formula	References
Root means square error (RMSE)	The root mean square error is the square root of the mean squared difference between	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{Forecast} - I_{Measured})^2}$	[163, 164]

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	predicted and observed values. It gives greater weight to large deviations, is sensitive to outliers, and is expressed in the units of the predicted variable.		
Mean absolute error (MAE)	Mean absolute error is the average absolute difference between predicted and observed values. It provides a direct measure of typical error magnitude without considering the direction of the error.	$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\lvert I_{Forecast} - I_{Measured}\rvert$	[163, 164]
Mean bias error (MBE)	Mean bias error measures the average signed difference between predicted and observed values. A positive value indicates overestimation, whereas a negative value indicates underestimation.	$\mathrm{MBA} = \frac{1}{N}\sum_{i=1}^{N}(I_{Forecast} - I_{Measured})$	[163, 164]
Relative RMSE	Relative RMSE is a normalized form of RMSE that scales the error to a	$\mathrm{rRMSE} = \frac{\mathrm{RMSE}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} I_{Measurement}^2}}$	[163, 164]

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reference value, such as the mean or range of the observations, thereby facilitating comparison across datasets.

AI-based forecasting in wind-energy systems

The uncertain and variable nature of wind, together with growing demand for renewable electricity, has increased the need for accurate and efficient wind-energy prediction [165] models [129]. AI techniques are valuable in wind-energy systems because they can represent the nonlinear and stochastic behavior of wind and often improve accuracy compared with conventional approaches [166] Machine-learning and deep-learning models can capture complex temporal patterns and variability that traditional statistical methods may not represent effectively [167]. Artificial neural networks, including autoregressive and hybrid variants, have been widely applied to wind-speed forecasting using historical meteorological [168]. Advanced deep-learning architectures, including LSTM and attention-based models, can improve short-term wind-power forecasts by integrating [169] meteorological inputs and optimized model parameters [133]. ANN and support-vector models also provide flexible approaches for incomplete or uncertain wind [170]. Hybrid and ensemble frameworks are therefore important for improving grid stability and the integration of wind energy into modern power systems [171].

The performance of wind energy forecasting models is highly dependent on the selection of meteorological input variables that accurately describe atmospheric conditions governing wind behavior. Among these, wind speed is the most significant predictor because wind turbine power output is proportional to the cube of wind speed, making even small variations greatly influence energy generation. Wind direction is another essential variable as it determines the orientation of wind flow relative to the turbine rotor and significantly affects wake interactions and power production. Air density, which is influenced by atmospheric pressure, temperature, and humidity, directly affects the kinetic energy available in the wind and consequently the power extracted by wind turbines. Atmospheric pressure provides information about pressure gradients that drive wind formation and is widely used to improve numerical weather prediction (NWP) and machine learning models. Ambient temperature influences air density and atmospheric stability, thereby affecting wind characteristics and turbine performance. Furthermore, atmospheric turbulence plays a critical role in short-term wind forecasting because turbulent fluctuations alter wind speed, increase mechanical loads on turbines, and contribute to forecasting uncertainty. Recent studies have shown that integrating these meteorological variables into artificial intelligence models, including artificial neural networks (ANNs), support vector regression (SVR), long short-term memory (LSTM) networks, and hybrid deep learning approaches, substantially improves forecasting accuracy across short-, medium-, and long-term

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prediction horizons by capturing the complex nonlinear interactions between atmospheric dynamics and wind power generation [172-177].

4.6.1. Artificial neural network

Artificial neural networks are widely used for wind-speed forecasting because they can learn nonlinear relationships between meteorological inputs and wind output. Variables such as wind speed, direction, temperature, and pressure are supplied as features to predict future wind speed or power. A typical ANN consists of an input layer, one or more hidden layers, and an output layer connected through weights that are adjusted during training [172, 178]

Table 4. Mathematical expressions for ANN-based wind forecasting

Mechanism	Equation of function	References
Input-to-hidden-layer weighted sum The net input to a neuron is calculated as a weighted sum of the input features. This expression represents how the learned weights determine each input's contribution to the neuron output	$u_k = \sum_{i=1}^{n} w_{ki} x_i$	[179]
Addition of bias A bias term is added to improve model flexibility by shifting the activation function	$v_k = \sum_{i=1}^{n} w_{ki} x_i + b_k$	[179]
Activation function A nonlinear activation function transforms the weighted input. Common choices include the sigmoid, rectified linear unit (ReLU), and hyperbolic tangent functions	$y_k = f(v_k)$	[180]
Hidden-to-output layer The output layer produces the predicted wind speed	$y = f\left(\sum_{j=1}^{m} w_j h_j + b\right)$ where h_j are hidden layer outputs.	[181]
Error function (training) Prediction error is commonly calculated using mean squared error (MSE), which is minimized during training	$E = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)\,\hat{}\,2$	[182]

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Weight-update rule (backpropagation) Weights are updated using gradient descent. where ηis the learning rate controlling convergence speed	$w^{new} = w^{old} - \eta \frac{\partial E}{\partial W}$	[183]

4.6.2. Support vector regression for wind forecasting

Support vector regression is a powerful machine-learning method for wind forecasting because kernel functions allow it to represent nonlinear relationships in a higher-dimensional feature space. SVR has strong generalization ability and is comparatively resistant to overfitting, particularly for limited or noisy datasets. Its structural-risk-minimization framework can support accurate forecasts across different [184-186]

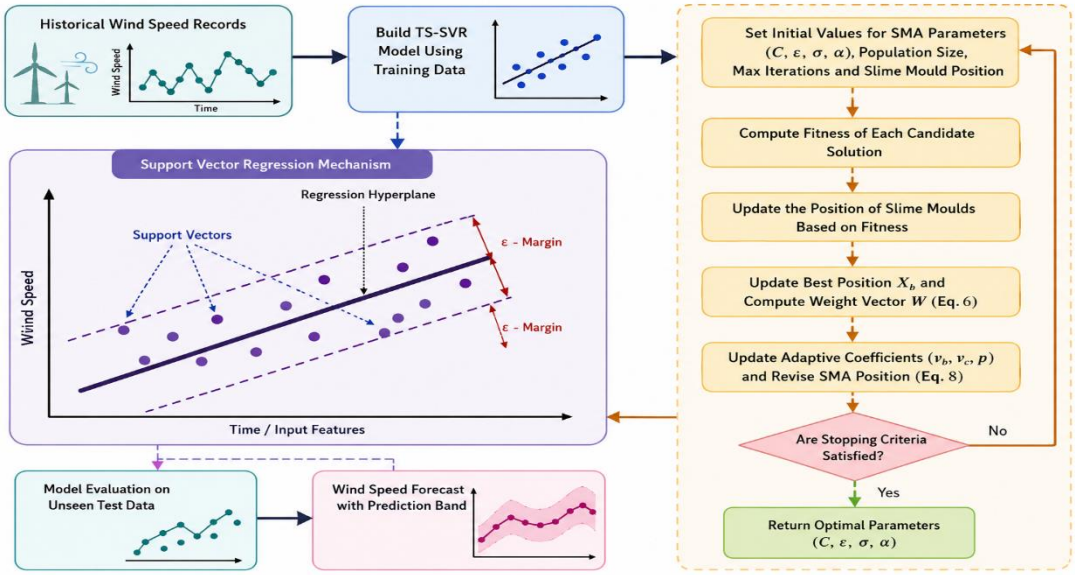

Figure 4. Support vector regression mechanism for wind forecasting

Table 5. Mechanism of support vector regression in wind forecasting

Functional component	Mathematical expression	References
Regression function SVR estimates wind output using a nonlinear regression function	$f(x) = w^T \emptyset(x) + b$ $\phi(x)$ is mapping to higher-dimensional space, w is weight vector and b is bias term.	[184]
Optimization objective SVR balances model complexity with prediction error to improve generalization	$\min 21 \| w \| 2 + Ci = 1 \sum N(\xi i + \xi i *)$ Here, C is penalty parameter and ξ_i, ξ_i^* are slack variables	[185]

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Errors within a specified tolerance are ignored, making SVR comparatively robust to small fluctuations in wind data	$\mid y - f(x) \mid \leq \varepsilon$	[187]
Kernel function (nonlinear mapping) Kernel functions enable SVR to represent nonlinear wind patterns without explicitly computing the high-dimensional mapping	$K(xi, xj) = \phi(xi)T\phi(xj)$ A commonly used radial basis function kernel is: $K(xi, xj) = \exp(-\gamma \mid\mid xi - xj \mid \mid \hat{}2)$	[188]
Final prediction function Only the support vectors contribute directly to the final prediction, making the resulting regression function efficient	$f(x) = i = 1\sum N(\alpha i - \alpha i *)K(xi, x) + b$	[189]

4.6.3. Gaussian process regression

Gaussian process regression is a probabilistic machine-learning method that models the relationship between meteorological inputs and wind power while quantifying predictive uncertainty. It treats the target as a stochastic process and uses covariance functions to measure similarities among past and future wind conditions. GPR produces a predictive mean and variance, which are valuable for grid-stability analysis and renewable-energy [190-193].

The final forecast output, represented by the predictive mean of the Gaussian process, is:

$$\mu(x_*) = K(X_*, X)[K(X, X) + \sigma_n^2 I]^{-1} y$$

Table 6. Performance metrics for AI-based wind-power forecasting

Evaluation metrices	Formula	References
Root mean square error is the square root of the average squared difference between predicted and observed values. It gives greater weight to large errors and is widely used to evaluate wind-power forecasts	$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)\hat{}2}$	[194]

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Mean absolute percentage error is the average absolute error expressed as a percentage of the observed value.

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i}{y_i} - \frac{\hat{y}_i}{y_i}\right| . 100\% \quad [195]$$

Mean squared error is the average squared difference between predicted and observed values. Squaring prevents positive and negative errors from cancelling one another and penalizes large deviations.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)\text{^}2 \quad [195]$$

Prediction interval normalized average width measures the average width of a prediction interval after normalization. It is used together with coverage to evaluate the sharpness of probabilistic forecasts.

$$\text{PINAW} = \frac{1}{N}\sum_{i=1}^{N}\frac{(U_i - L_i)}{t_{max} - t_{min}} \quad [196]$$

Mean bias error is the average signed forecast error. Negative values indicate underestimation, whereas positive values indicate overestimation.

$$\text{MBE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i) \quad [195]$$

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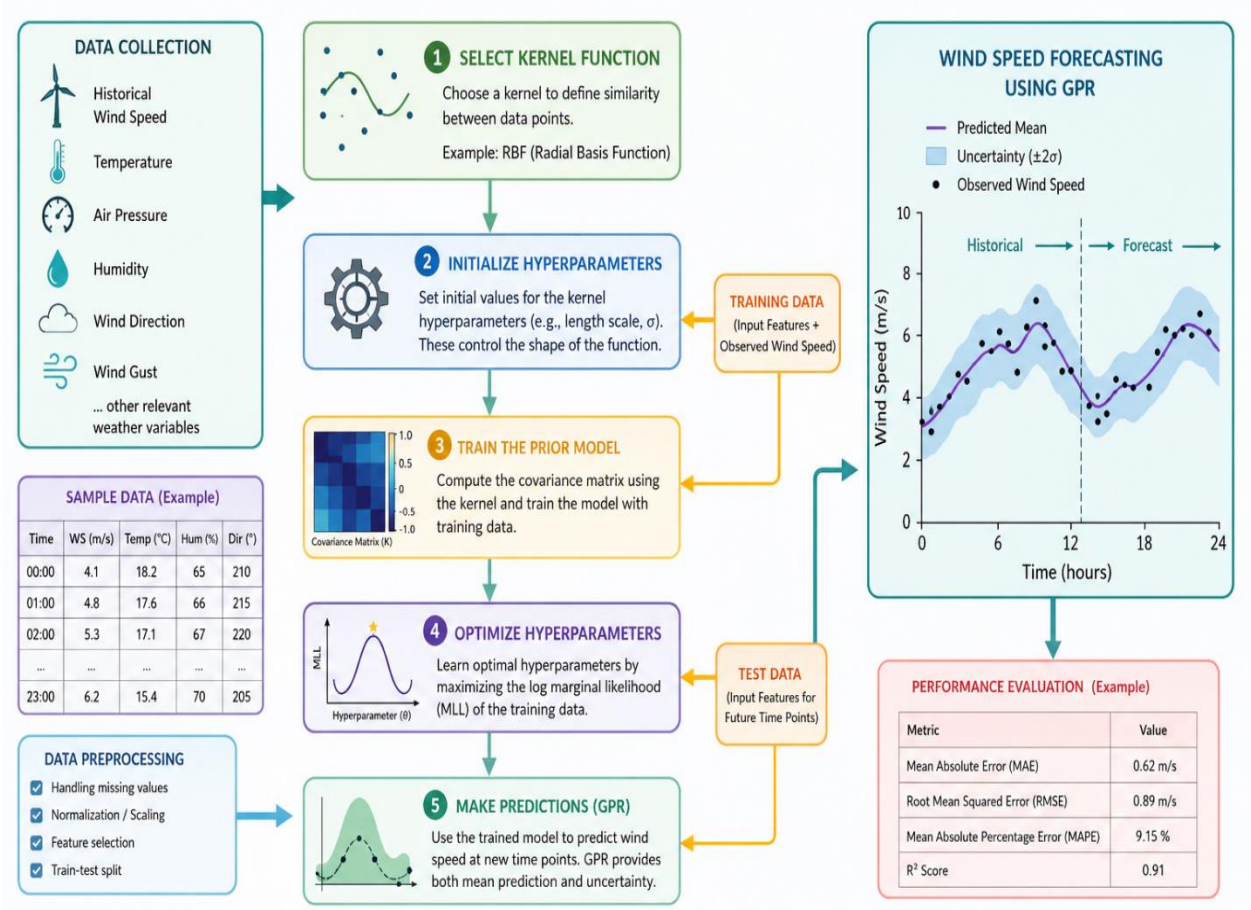

Figure 5. Gaussian process regression for wind forecasting

AI-based forecasting in hydropower systems

AI techniques, including machine-learning and deep-learning models, can represent complex nonlinear relationships among rainfall, river inflow, reservoir levels, and hydropower output that are difficult to capture with conventional statistical approaches. In hydropower applications, these models are used to forecast generation, consumption, and hydrological conditions, thereby supporting operational planning and system stability. Integrating AI with climate and hydrological data can also improve assessments of climate-change impacts on hydropower productivity. Hybrid frameworks that combine data-driven and physical models may improve predictions of hydroclimatic processes and reservoir inflows. Overall, AI offers adaptable and efficient tools for optimizing hydropower generation and integration into modern [19, 23, 197-199].

The accuracy of hydropower forecasting models depends on the selection of hydrological and meteorological input variables that represent the dynamic behavior of a river basin and reservoir system. River flow (streamflow) is the most important input because it directly determines the volume of water available for power generation and strongly influences turbine output. Reservoir inflow provides information about the amount of water entering the reservoir from upstream catchments and is essential for

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reservoir operation, scheduling, and energy production planning. Rainfall (precipitation) is a key driving factor affecting runoff generation and future streamflow, making it indispensable for short- and medium-term hydropower forecasting. Water level in rivers or reservoirs reflects the current storage conditions and hydraulic head available for electricity generation, thereby influencing turbine efficiency and operational decisions. In addition, sediment level (sediment concentration or sediment load) significantly affects hydropower performance by reducing reservoir storage capacity, increasing turbine wear, and altering flow characteristics, making it an important variable in long-term forecasting and maintenance planning. Recent studies have demonstrated that integrating these hydrological variables with artificial intelligence techniques, such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), Long Short-Term Memory (LSTM), Gaussian Process Regression (GPR), and hybrid deep learning models, substantially improves forecasting accuracy by capturing the complex nonlinear relationships between watershed processes and hydropower generation [200-205].

Gaussian process regression–cooperation search algorithm hybrid model

The hybrid GPR–CSA model is a probabilistic learning framework designed for nonlinear and nonstationary hydrological systems, including river inflow and hydropower generation. Gaussian process regression models the stochastic relationship between inputs, such as rainfall, temperature, and antecedent runoff, and the target output. The cooperation search algorithm optimizes GPR hyperparameters to improve accuracy and reduce the risk of convergence to local optima. Because GPR defines a distribution over functions, it supports both point prediction and uncertainty quantification. Combining it with CSA can improve generalization in complex hydroclimatic datasets [190, 206-208].

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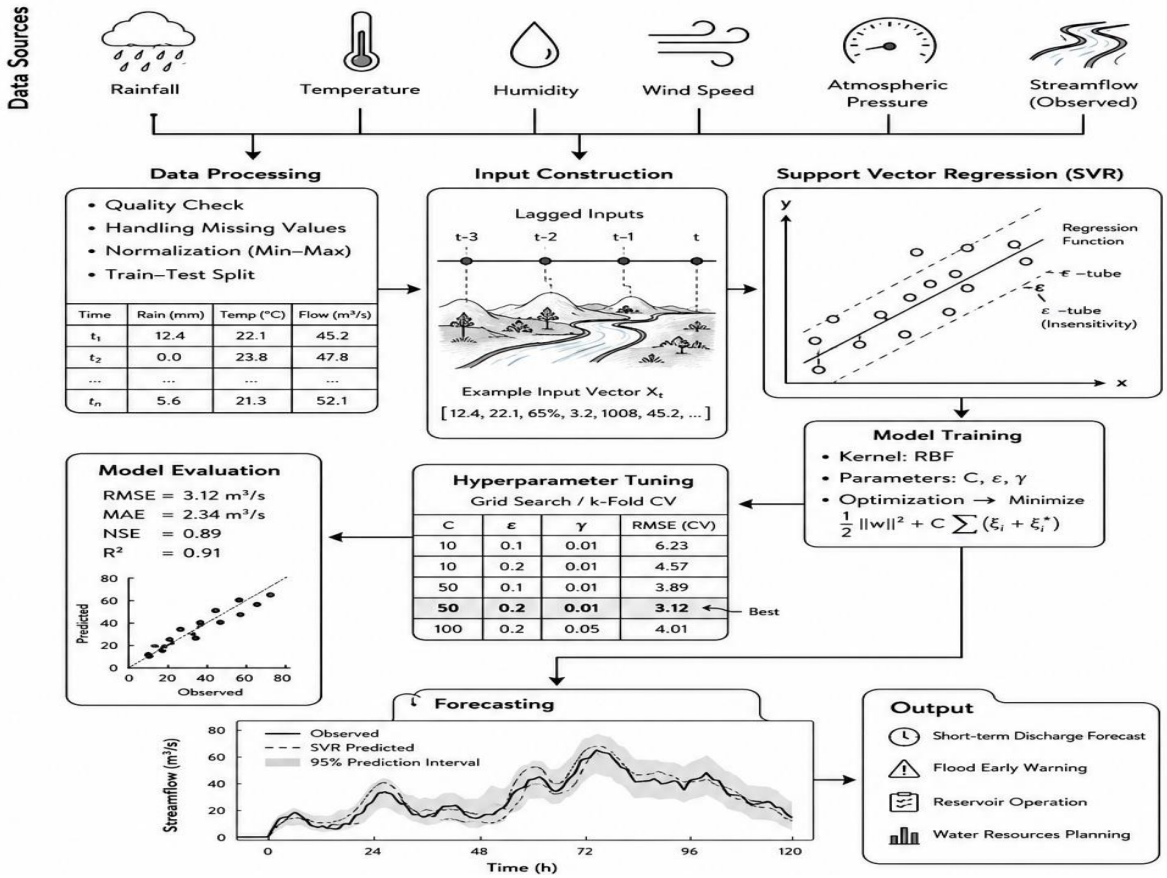

Figure 6. Step-by-step representation of the GPR–CSA model

Table 7. Mechanism of the GPR–CSA hybrid model in hydropower forecasting

Functional component	Mathematical expression	References
Gaussian-process prior Defines a stochastic function space in which predictions follow a Gaussian distribution	The probabilistic Gaussian-process prior used in hydrological forecasting is: $f(x) \sim GP(m(x), k(x, x'))$	[206]
Mean function Represents the expected runoff or hydrological output and is often assumed to be zero in practical applications	$m(x) = \mathbb{E}[f(x)]$	[209]

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Covariance or kernel function Encodes spatial and temporal dependence among hydrological variables. The choice of kernel can substantially affect accuracy	$k(x, x') = \mathbb{E}[(f(x) - m(x))(f(x') - m(x'))]$	[210]
Squared-exponential kernel Captures smooth nonlinear relationships in runoff and groundwater prediction	$k(x, x') = \sigma\text{^}2\text{fexp}\left(\frac{\|x - x'\|\text{^}2}{2l\text{^}2}\right)$	[210]
Predictive-mean equation Provides the forecast streamflow or hydropower output and is widely used in hydrological GPR applications	$\hat{y} * = K(X_*, X)[K(X, X) + \sigma_n\text{^}2 I]\text{^} - 1y$	[206]
Predictive-variance equation Quantifies uncertainty in hydrological predictions and is important for risk-aware reservoir management	$\sigma_*\text{^}2 = K(X_*, X_*) - K(X_{*-} - X)[K(X, X) + \sigma_n\text{^}2 I]\text{^} - 1K(X - X_*)$	[211]
Log marginal likelihood (hyperparameter learning) Used to estimate GPR kernel parameters in Bayesian hydrological modelling	$\log_P(y\|X) = -\frac{1}{2}y^T(K + \sigma_n^2 I)^{-}1y - \frac{1}{2}\log\|K + \sigma_n^2 I\| - \frac{n}{2}\log 2\pi$	[212]

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CSA optimization equation
CSA searches for optimal hyperparameters and can improve GPR performance for nonlinear runoff forecasting

$$\theta^{t+1} = \theta^{t} + \alpha(best - \theta^{t}) + \beta \cdot rand() \quad [207]$$

Fitness function
Minimizes prediction error, commonly MSE, during optimization

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad [207]$$

Final hydropower-forecasting equation
Represents the final learned relationship between hydrological inputs and outputs

$$Q(t+1) = f(Q(t), Q(t-1), R(t), T(t)) + \epsilon \quad [206].$$

Here, Q is streamflow / inflow, R is rainfall, T is temperature and $\epsilon \sim \mathcal{N}(0, \sigma^2)$.

Support vector regression for hydropower forecasting

Support vector regression is widely used to forecast streamflow, reservoir inflow, and floods because it can represent nonlinear relationships and is mathematically simpler than many deep-learning architectures. It identifies a function that balances prediction error and model complexity, supporting generalization in nonlinear hydrological [213, 214].

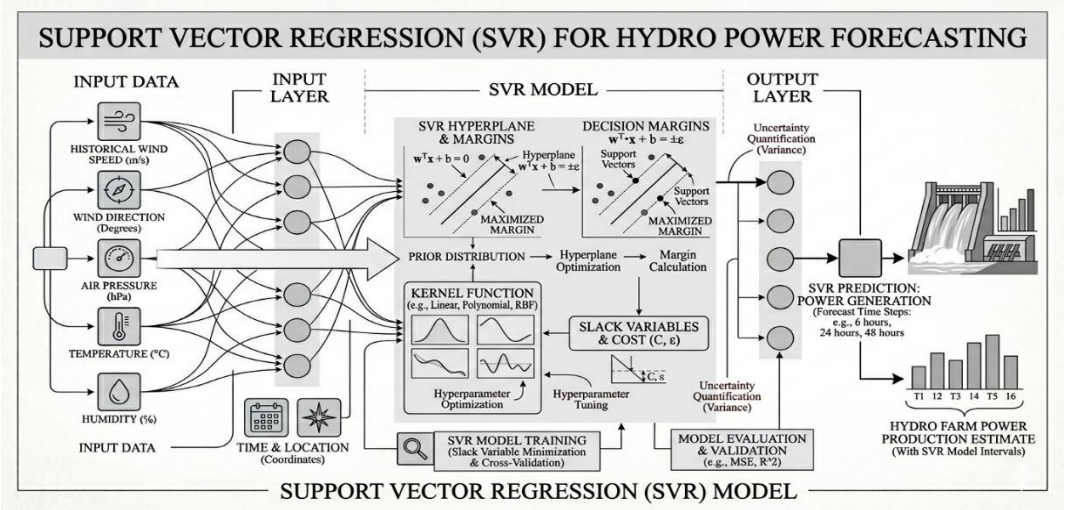

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Figure 7. Support vector regression for hydropower forecasting

Table 8. Mechanism of support vector regression in hydropower forecasting

Functional component	Mathematical expression	References
Input–output relationship Lagged variables are selected according to the response time of the hydrological system	Hydrological forecasting with SVR can be expressed as: $Q_t = f(Q_{t-1}, R_{t-1}, T_{t-1}, S_{t-1})$ Here, Q_t is streamflow at time t, Q_{t-1} is previous discharge, $R_{t-1}$is rainfall T_{t-1} is temperature and S_{t-1}= snow or another hydrological variable	[214]
SVR regression function This linear form defines the regression function in the transformed feature space	The SVR prediction function is: $f(x) = w^T x + b$ Here, w is the weight vector, x is the input vector, and b is the bias term.	[215]
Nonlinear transformation using a kernel Kernel functions enable SVR to represent complex rainfall–runoff relationships	To model nonlinear hydrological processes, SVR uses kernel functions such as: $f(x) = \sum_{i=1}^{n} (a_i - a_i^*) k(x_i, x) + b$	[213]
Radial basis function kernel The radial basis function is widely used in hydrology because it can represent nonlinear streamflow behavior	$K(xi, x) = \exp(-\gamma \parallel xi - x \parallel^2)$ Here, γ is the kernel parameter.	[216]
Optimization objective The optimization objective follows the structural-risk-minimization principle and supports generalization in hydrological prediction	$\min\left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)\right)$ SVR training is based on minimizing: Subject to: $\| y_i - f(x_i) \| \leq \varepsilon$ here, C is penalty factor, ε is error tolerance and ξ_i are slack variables.	[213]

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SVR parameters such as Cand γ are typically selected using grid search optimization techniques to improve prediction accuracy [215]. SVR effectively predicts daily and multi-step streamflow, performs well for flash flood forecasting with short lead times and also shows lower uncertainty and better generalization than ANN in some groundwater studies [214-216].

$$Q_{t+1} = f(Q_t, R_t, T_t)$$

Here, Q_t is current flow, R_t is rainfall, $T_t$is temperature and Q_{t+1} is predicted flow and this equation is used in real studies for 48-hour streamflow prediction [217].

Table 9. Evaluation metrics for hydropower generation forecasting

Evaluation metrics	Formulas	Reference
Correlation coefficient	$R = \frac{\sum(x_i - \bar{x})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$	[218]
Root means square error	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$	[170,171]
Mean squared error	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$	[219]
Mean absolute error	$MAE = \frac{\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert}{n}$	[202]
Mean absolute percentage error	$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left\lvert\frac{\hat{X}_t - X_t}{X_t}\right\rvert$	[204]

Comparative analysis of AI forecasting techniques for solar, wind, and hydropower systems

Solar, wind, and hydropower generation depend on environmental conditions, making their output variable and uncertain. Accurate forecasts are essential for grid stability and energy management. Because conventional statistical models may struggle with nonlinear behaviour, AI methods are increasingly used to represent complex relationships [172]. Renewable-energy [220] forecasting can be expressed generally as:

$$P_t = f(X_t, X_{t-1}, \ldots\ldots, \theta)$$

Here, P_t is power output, X_t is meteorological and historical inputs and θ is model parameter. However, heterogeneity in input dynamics fundamentally differentiates solar, wind, and hydro systems with solar is affected by deterministic and cloud-induced stochasticity, wind forecasting demands investigation on chaotic turbulence and spatial coupling and wind RESs requires delayed, memory-driven hydrological processes. This leads to distinct AI model behavior across domains [23], [221].

Solar irradiance follows a predictable diurnal pattern but is disrupted by cloud cover, creating a combination of deterministic and stochastic behavior. It has a quasi-periodic daily cycle, strong short-term autocorrelation, and medium-to-high short-term predictability [127,174]. Wind is more [163, 222] and turbulent and is therefore

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generally less predictable than solar generation [135]. Hydropower [171] governed by delayed hydrological processes and often displays smoother dynamics and greater temporal [23, 223, 224]. Solar forecasting combines meteorological, ground-based, and satellite data. Wind forecasting often requires measurements at multiple heights and locations because of terrain and wake effects. Hydropower forecasting relies primarily on hydro-meteorological variables and catchment or [163, 225-227]. Deep-learning models, including LSTM and CNN architectures, are widely used in solar forecasting because they can extract temporal and spatial features. Wind forecasting often benefits from hybrid CNN–LSTM models that combine spatial and temporal learning. Hydropower forecasting can perform effectively with models such as SVM and ANFIS when the underlying dynamics are [171, 228-230]. Solar-forecasting studies report strong performance from transformer, CNN–LSTM, and LSTM models because solar generation depends on temporal weather patterns, including irradiance, cloud movement, and temperature. In wind forecasting, GRU, bidirectional LSTM, transformer, and hybrid models can reduce errors relative to conventional ANN, SVM, and random-forest approaches. Hydropower forecasts depend on rainfall, river discharge, reservoir levels, and catchment characteristics; random forest and XGBoost perform well in many applications, while LSTM models are particularly useful when long hydrological records are available [222, 231, 232].

Solar forecasting requires irradiance, temperature, humidity, cloud cover, and photovoltaic-output data. Deep-learning models generally require large datasets for effective training. Wind forecasting uses wind speed, direction, atmospheric pressure, and temperature, often at high temporal resolution because wind conditions change rapidly. Hydropower forecasting relies on precipitation, river flow, reservoir level, snowmelt, and meteorological records, with seasonal information playing an important [22] role [233, 234]. Transformer and CNN–LSTM models can provide high accuracy but require substantial computational resources and training time. Wind-forecasting models may demand additional computation because of highly dynamic and spatially complex wind patterns. Hybrid models can also be computationally intensive. Hydropower models may require less complexity when seasonal and hydrological persistence dominate the [235, 236]. Solar-forecast accuracy decreases under cloudy and rapidly changing weather conditions, although hybrid transformer–LSTM models may improve robustness. Wind forecasting faces substantial uncertainty, making ensemble and hybrid approaches useful for reducing error. Hydropower is comparatively stable because many hydrological variables change gradually, but extreme rainfall and drought can still reduce [237-239].

Deep-learning models often outperform conventional machine-learning approaches when sufficient high-quality data are [240]. Hybrid models frequently achieve high forecasting accuracy by combining complementary [241]. Solar output is generally more predictable than wind output over comparable short-term horizons [242]. Wind forecasting often requires more complex spatial and temporal [171]. Hydropower forecasting remains less extensively studied than solar and wind [234].Transformer models are an important emerging approach [235]. Data quality can be more important than model complexity [243]. Multi-site models can outperform single-site forecasts by exploiting spatial information [222]. Limited explainability remains a major barrier to

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operational deployment [244]. Recent research is exploring foundation models and large-scale transformers [245].

FUTURE DIRECTIONS

Future research on AI forecasting for solar, wind, and hydropower systems should emphasize hybrid and physics-informed models that combine machine learning with meteorological, hydrological, and physical-system knowledge. LSTM, GRU, CNN, and transformer architectures can improve forecast accuracy, but their performance may be strengthened by incorporating numerical weather predictions, satellite imagery, and real-time sensor data. Explainable AI and uncertainty-quantification methods are also needed to improve transparency and reliability for grid operators and energy planners. Another important direction is the integration of AI forecasting with smart grids, Internet of Things devices, edge computing, energy storage, and digital twins. Decentralized forecasting, federated learning, and AI-based decision-support systems may enable real-time management of renewable resources across large power networks. Reinforcement learning and large language models may also support adaptive forecasting, predictive maintenance, and automated energy management, provided that their reliability, computational cost, and operational safety are carefully evaluated.

Furthermore, the Deep Learning-based short-term, dynamic and linearized forecasting algorithms will identify unstable operation conditions very early along with correctness, resilience and transferability across various grids when RESs is collaborated with physics-based power system model with data-driven AI. In order to imitate real-world energy network with dynamic stability evaluation, fault-scenario analysis and anticipatory control strategy AI-powered Digital Twins can be used. Moreover, Federated Learning-Edge AI to learn smart grid conducts, AI-Driven Virtual Inertia and Grid-Forming control strategies to improve steady-state security and disturbance ride-through capability, use of Explainable AI to support decision-making in grid functions, Hybrid AI for resilience, Cyber-Physical Security and AI-based Fault-Detections for fast pinpointing of hackings, integration of AI with market and stability market and Standardization and real-world deployment by focusing Hardware-in-the-Loop (HIL), benchmark datasets and standard test systems, all the AI-models and algorithms will increasingly focus on bridge between AI-Algorithms and practical grid implementations.

CONCLUSION

Artificial intelligence has become an important technology for forecasting and managing solar, wind, and hydropower generation. As renewable penetration increases, variability and weather dependence create challenges for power-system operation. Accurate forecasts are therefore essential for grid stability, production optimization, cost reduction, and energy planning. Machine learning, deep learning, artificial neural networks, LSTM, random forest, and hybrid models can outperform conventional statistical approaches by representing complex nonlinear relationships in environmental and operational data.

Solar, wind, and hydropower present distinct forecasting challenges. Solar generation depends on irradiance, cloud movement, and atmospheric conditions; wind generation

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is affected by highly variable wind speed and direction; and hydropower depends on rainfall, river flow, reservoir levels, and catchment conditions. AI-based approaches improve prediction across these domains by using historical records, real-time monitoring, and advanced computational methods. Sequence models, including LSTM and GRU, are particularly useful when long-term temporal dependencies are important. AI also supports predictive maintenance, fault detection, energy optimization, and smart-grid integration. Its ability to process large volumes of meteorological, operational, and sensor data enables more efficient management of renewable-energy infrastructure. Integration with energy storage, Internet of Things devices, and cloud platforms is contributing to intelligent energy systems that can respond dynamically to fluctuations in generation and demand.

Important challenges remain, including data quality, model interpretability, cybersecurity, computational complexity, and the absence of standardized benchmarking frameworks. Future research should emphasize explainable AI, hybrid forecasting architectures, federated learning, uncertainty quantification, and real-time deployment. Emerging technologies, including reinforcement learning, digital twins, and large language models, may further improve forecasting and decision-making. Overall, AI-based forecasting is an important enabler of reliable and sustainable renewable-energy systems.

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