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Review Article

Solar Forecasting Methods: Transition from Classical to Artificial Intelligence-based Forecasting

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Abstract The variability in photovoltaic power generation generates different negative effects on power grid systems in terms of stability, reliability, and operation planning. Therefore, an accurate estimation of PV power generation is crucial for stabilizing and securing grid operation and promoting large-scale PV power integration. Every year, new techniques and approaches emerge worldwide that reduce the uncertainty in these estimates and improve model accuracy. This study presents a comprehensive survey of solar energy prediction models while summarizing the most recent methodologies and strategies employed to enhance the precision of solar energy production forecasting. The energy sector is highly dynamic and integrates new technologies continually; hence, compilation studies should be updated with new developments. Industries are trying to benefit from artificial intelligence, including the field of solar energy prediction, and this study attempts to capture this trend. In addition to presenting a comparison of the solution methods in artificial intelligence, hybrid approaches to overcome problems are discussed. Different classification models and critical analyses of recent studies based on forecast horizons and historical data are also presented.

Keywords: Classifications; day-ahead forecast; forecast horizon; historical data; PV power generation; solar forecasting

1. INTRODUCTION

Throughout the last two millennia, human actions have been the principal driver behind an unprecedented temperature increase on Earth, leading to the accumulation of greenhouse gases [1]. Energy plays a vital role as a valuable resource [2] and is a crucial factor in a country's development [3]. As societies progress, the need for energy rises, resulting in the utilization of diverse conventional energy resources. Regrettably, non-renewable energy sources are responsible for the emission of greenhouse gases and environmental deterioration [4].

The Paris Agreement, a global initiative aimed at combating climate change, witnessed the participation of representatives from 196 countries. At this conference, they pledged to limit global warming to an increase of less than 2°C. This resolution establishes the goal of attaining net-zero greenhouse gas emissions by the close of the 21st century. Among the essential actions called for in this agreement is the electrification of existing thermal systems. Emphasizing the need to generate energy from renewable sources, the agreement also drives research on effectively managing and integrating these variable generation systems aboard the power grid [5].

Transition of the global energy system is crucial because energy consumption is responsible for most of the global greenhouse gas emissions [6]. A shift towards low-carbon energy sources is bringing about a fundamental transformation in the global energy landscape, with renewable energy now accounting for over 27% of electricity production [7]. To ensure a balanced supply and consistent production, many countries are heavily investing in renewable energy sources, which augments their prospects in the near future [8]. Notably, the extensive growth in renewable power generation has significantly reduced coal consumption, as depicted in Figure 1.

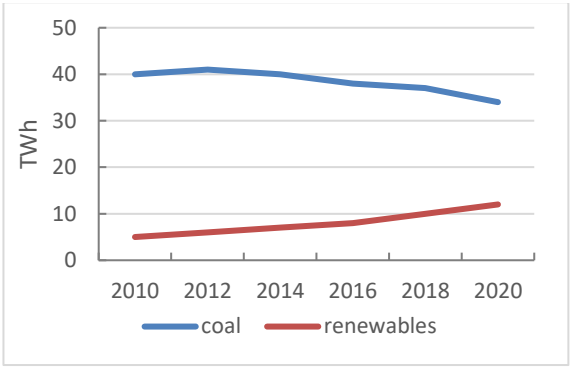


Figure 1. Share of renewables and coal in global energy production

Wind and solar power have experienced a remarkable surge in the last five years, contributing to approximately 60% of the global electricity production growth. The data presented in the Figure 2 reflects the global annual capacity additions reported by IRENA and the IEA. The figures illustrate a significant acceleration in solar PV deployment, which reached a record 453 GW in 2024. According to Ember's recent analysis, this rapid expansion is the primary driver behind the global shift toward a decarbonized power sector, with solar and wind together now providing the majority of new generating capacity. As fossil fuel reserves continue to deplete and the energy crisis looms, incorporating sustainable energy sources into smart grid infrastructure becomes indispensable [9]. Furthermore, the declining production costs of electricity from renewable sources compared to fossil fuels have also contributed to their rapid adoption in recent years.

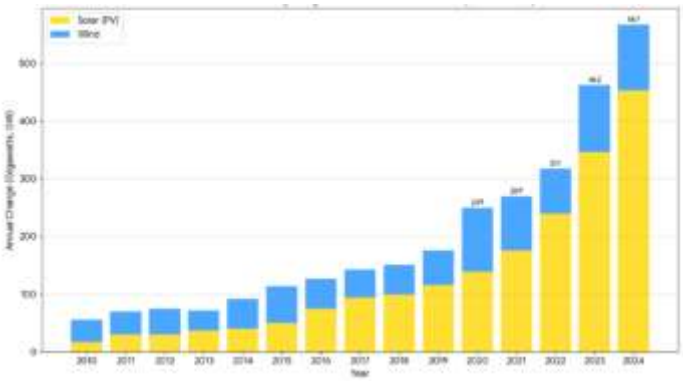


Figure 2. Global Annual capacity for solar and wind

In the context of growing global energy demands, alternative and renewable energy sources have garnered widespread attention [10]. Driven by government policies and incentives, these sources are expected to gain further popularity in the future, primarily due to their abundant availability and environmental sustainability [11]. Solar energy has emerged as the most economically viable option in human history for generating electricity [7]. Photovoltaic (PV) power plants have received substantial attention due to their accessibility, low maintenance and operational costs, long lifespan, and eco-friendly nature [12]. Solar energy offers distinct advantages over other renewable energy sources in meeting the electricity demands of residential and commercial buildings due to its ease of installation, diminished dependence on extensive infrastructure, and cost-efficiency [13].

Solar PV integration has become prevalent in many countries worldwide. As solar PV plants continue to expand through grid connections or standalone networks, substantial changes are expected in power system process and design. The integration of solar PV necessitates the management of power output uncertainties and fluctuations. Therefore, accurate solar PV power estimation assumes critical importance in facilitating optimal planning and modeling of solar PV plants. Reliable forecasting emerges as one of the most viable approaches to address the uncertainty in solar energy availability [14]. These insights are crucial for grid operators and power system designers as they strive to effectively oversee power supply, fulfill demand needs, and formulate efficient designs for solar PV facilities [15].

To ensure effective utilization of PV generation, estimating solar radiation based on limited available information becomes essential [16]. Table 1 provides a compilation of literature reviews on PV power estimation. Based on various factors, researchers have classified the estimation of PV power generation into distinct categories, but a standardized criterion for classifying PV power forecasting does not currently exist.

Table 1. Reviews on PV power forecasting.

Description	Description
[15] It covers various aspects of the field, including modelling and planning, spatial and temporal horizons, and smart grid forecasting. The article also discusses the benefits of accurate forecasting for grid operators and power system designers.	[18] This article is a review of the latest technologies and strategies for optimizing solar PV generation in microgrids, with a focus on nowcasting and very short-term forecasting. It discusses the challenges associated with integrating solar PV into microgrids, the key technologies and tools used for nowcasting solar irradiance, and how nowcasting can be used to optimize the operation of distributed energy resources (DERs) in microgrids.
(Akhter et al., 2019) This article is reviewing the current state of forecasting photovoltaic power generation using machine learning and metaheuristic techniques. The article discusses the importance of renewable energy sources, particularly solar energy, in meeting the world's energy demand and reducing global warming. It also provides a critical analysis of various mathematical techniques, including machine learning techniques such as ANN, SVM, and ELM, and metaheuristic techniques, and compares their advantages and disadvantages.	[5] This article is highlighting the challenges posed by the variability of solar resources and underscores the need for accurate forecasting to ensure grid stability, optimize unit commitment, and enable cost-effective energy distribution. It also emphasizes various forecast horizons and spatial scales involved in solar power forecasting, ongoing advancements in forecasting techniques, and the growing importance of probabilistic predictions. Additionally, it presents the economic implications of accurate forecasts and provides a classification of forecasting studies based on different criteria. Finally, it addresses the need for standard metrics to facilitate fair comparisons among research studies in this field.
[20] This article is explaining the increasing complexity of accurate forecasting in the face of more photovoltaic systems and unpredictable electricity usage, like electric vehicles. The paragraph discusses the shift from deterministic to probabilistic forecasting in solar power and load forecasting, aiming to assess different approaches' performance and the need for standardization in data handling and metrics.	[12] ln this article, the increasing adoption of renewable energy resources, particularly photovoltaic (PV) electricity generation, over the last decade due to environmental concerns and its economic advantages. However, the uncertainty in PV output power, driven by meteorological factors, poses challenges for the power grid and necessitates accurate forecasting. The text discusses the need for precise PV output forecasts across various time scales and presents a comprehensive review of PV output power forecasting models, including factors influencing forecasts, performance metrics, and analyses of regression-based and artificial intelligence-based models. It also explores the potential benefits of hybrid forecasting techniques for PV.
[21] ln this article, the challenges of integrating solar energy into power grids due to its dependence on weather conditions. The text emphasizes the importance of accurate forecasting models to mitigate issues like voltage surges and system instability. It discusses factors like input correlation, data preprocessing, and performance metrics. Different forecasting techniques are reviewed, highlighting the effectiveness of ensemble artificial neural networks for short-term forecasts and other methods for specific needs. Overall, it provides insights into improving photovoltaic power forecasting, particularly through hybrid neural networks and evolutionary algorithms.	[22] Description of this article is revolving around the challenges posed by the intermittent and volatile nature of solar photovoltaic (PV) power generation due to its reliance on solar radiation and weather conditions. It highlights the negative impact of grid-connected PV systems on power grids and the need for accurate forecasting, flexible planning, and operational measures. The text reviews studies in three key areas: (1) forecasting techniques for PV power generation output, (2) the impact of high solar generation on grid frequency stability and methods for PV participation in frequency regulation, and (3) measures to facilitate the consumption of intermittent solar power across regions. It concludes by discussing future challenges and areas of focus in the development of power grids and PV power generation.
[23] In this article, discusses the importance of accurate PV output power forecasting for grid integration, particularly in the context of AI techniques like ML and DL.	[24] This article compares two PV power forecasting methods based on Artificial Neural Networks. One relies solely on available data, while the other uses weather forecasts. The first method is stable on sunny days (NMAE% 1-2%), while the hybrid method excels on some days but is less consistent (NMAE% >2% and up to 5.3%). On cloudy days, both methods see reduced accuracy, with the non-weather-dependent method showing more stability.
[25] This paper discusses forecasting tools for short-term PV power in large-scale grid-connected farms. Solar energy is vital, and PV farms are expanding globally. Accurate forecasting is essential due to PV's weather dependence. The best approach involves predicting irradiance and cell temperature and using various data sources, like satellites and sky imaging, for precise short-term forecasts.	[26] This study compares day-ahead PV power forecasts using deterministic and stochastic models. Deterministic models showed similar accuracy, while a hybrid method with artificial neural networks performed the best, requiring minimal training for accurate predictions, based on data from a Milan PV plant.

PV power forecasting is frequently categorized by researchers according to factors such as time horizon, historical solar radiation data, and the forecasting methods utilized [17]. This article offers an extensive examination of PV power generation estimation, with a particular emphasis on diverse classifications within the domain. Specifically, the review examines forecasting methods based on time horizons and historical data, with a particular emphasis on the utilization of artificial intelligence (AI) models in PV forecasting. Moreover, the article discusses the limitations of these techniques and proposes a hybrid approach to overcome these challenges.

This work reflects the ongoing shift in PV forecasting research from traditional models to data-driven and intelligent systems, thus providing a timely and forward-looking assessment of this field.

The remainder of this paper is organized as follows: Section 2 introduces studies focused on various future timeframes, referred to as time horizon-based forecasting. In Section 3, estimations based on historical data are elaborated upon, with subsections detailing the forecasting methods and models. Lastly, Section 4 provides the conclusion for this work.

2. FORECASTING BASED ON TIME HORIZON

The forecast horizon refers to the future period for which forecasts are made, and it significantly impacts the forecast accuracy of a model with the same parameters. Therefore, it is crucial to consider the forecast time horizon when designing an appropriate forecasting model. Although there are no well-defined criteria for classifying forecast models based on time horizon, the estimation of PV power generation is typically categorized into four groups:

- Intra-hour, day-ahead, or nowcasting forecasts.
- Short-term forecasts, for one hour to several hours ahead, up to one day or one week.
- Medium-term forecasts, spanning from one month to one year ahead.
- Long-term forecasts, for 1 to 10 years ahead.

Table 2 provides an overview of studies that classify PV power estimation based on the time horizon. Accurate very short-term (intra-hour or nowcasting) forecasts are crucial for ensuring secure and cost-effective operation of PV systems and effective grid energy management [27]. Forecasting in the very short term encompasses prediction windows ranging from a few seconds to a single hour, playing a crucial role in preserving grid integrity, stability, and the effective management of spinning reserves and demand response.

Hourly variability, primarily caused by cloud movements, significantly impacts the performance of solar power plants and electricity grids. Forecasting cloud-induced ramp-down events on clear days is particularly important for power system operators to ensure short-term reserve capacity. Real-time on-site irradiance estimation can assist operators in effectively managing PV plants [28].

The significance of solar irradiance in PV power systems cannot be overstated, given that the output power is directly linked to irradiance levels. Hence, precise solar irradiance forecasting stands as a pivotal requirement within PV power prediction systems. Nevertheless, during cloudy weather conditions, the forecasting precision of PV power is compromised due to irradiance fluctuations induced by cloud movements [29]. Modeling cloud movement is challenging due to their turbulent and seemingly stochastic nature [30].

Clouds, due to their dynamic and variable nature in terms of movement and thickness, constitute a crucial factor in the variability of PV power output. Furthermore, their movement velocities are utilized as an important input for short-term forecasting models. [31]. Continuous cloud observation can be achieved through two methods: ground-based and satellite measurements. Satellite images offer broader coverage but with lower detail, whereas ground-based sky observations using all-sky imagers provide higher temporal and spatial resolutions, although their coverage is limited [36].

Nowcasting systems employ remote sensing techniques to acquire data on cloud height and monitoring. Among these techniques, lidars and ceilometers are frequently employed for cloud height measurements. Lidars can capture data encompassing all layers from the cloud's base height (CBH) to its top height (CTH). In contrast, ceilometers offer insights into aerosol concentration within the atmosphere, while the Radio Acoustic Sounding System (RASS) is utilized to gauge the vertical temperature profile in the lower atmospheric layer [37].

Short-term forecasting models also encompass PV power generation forecasting, dispatch of electrical power, unit commitment, enabling the design of PV-integrated energy management systems and scheduling. These forecasts are essential for enhancing grid security [38]. Short-term forecasting encompasses prediction periods ranging from a few hours to as long as seven days. Various methodologies, including artificial neural networks (ANNs), support vector regression (SVR), regression models, and numerical weather prediction (NWP), can be applied, considering the numerous factors influencing PV power generation throughout the day.

Medium-term PV power forecasts span a timeframe of one week to one month. These forecasts play a critical role in anticipating future electrical power availability, enabling power system planning, and facilitating maintenance scheduling. They hold particular significance in the maintenance scheduling of both conventional and solar-integrated power systems equipped with advanced transformers and diverse electro-mechanical machinery [40]. Identifying the most effective predictors within this timeframe remains challenging, given the variety of techniques available, with the NWP model being a commonly employed approach.

Long-term forecasts for PV power generation encompass a timeframe from one month to one year. These forecasts hold a pivotal role in the strategizing of electricity generation, transmission, and distribution, as well as security operations. They also carry substantial importance in the context of energy auctions. However, due to the inherent difficulty in predicting weather fluctuations spanning multiple days or weeks, long-term forecasting models tend to have lower accuracy [40].

Table 2. Some studies on classifying PV power estimation by estimation horizon.

Ref	Forecast horizon	Forecast Method	Description	Data Source
[41]	Day ahead	NWP	This study involves the comparison of various data-driven models utilizing different Numerical Weather Prediction (NWP) input datasets. The objective is to then construct an improved multi-model ensemble (MME) and establish prediction intervals for more robust forecasting.	Experimental data NWP data Integrated Forecasting System (IFS) model of ECMWF
[42]	Day ahead	RBFNN, LS-SVM, kNN,	In this study, an analysis of the difficulties associated with solar power forecasting was conducted. Subsequently, a forecasting tool was introduced that operates on a similar-day basis, enabling the realization of 24-hour ahead forecasts specifically tailored for small-scale solar power output predictions.	240 Kyocera KD 205 GXLP PV modules BP 585 modules and BP GCI 1200 inverters
[43]	Day ahead	NWP	In this research study, a prediction methodology was introduced, which relies on the optimization of NWP data using the least squares technique. This approach was designed for forecasting both hourly average and day-ahead power output from power plants.	NAM data Route Data (File) Preparation System (RDPS) data
[44]	Day ahead	ANN	This study conducted a comparison of forecasting performance, particularly focusing on the commonly employed 24-hour ahead forecasting methods for estimating the power output of PV systems.	Experimental data
[45]	Day ahead	BPNN	In this study, a novel solar estimation approach was introduced. This method is designed for the day-ahead estimation of hourly solar irradiance and relies on the utilization of weather forecasting data.	Experimental data
[31]	Short-term forecasting	ANN	In this study, the goal was to estimate and predict the power output profile of a 20-kW grid-connected solar power plant situated in a well-established manufacturing industry in Tiruchirappalli, India. This was achieved using ANNs as the forecasting method.	Experimental data
[32]	Short-term forecasting	SOM LVQ SVR	In this research, a hybrid prediction model was introduced for forecasting PV power generation. The methodology involved the use of Self-Organizing Maps (SOM) and Learning Vector Quantization (LVQ) to classify historical data according to weather conditions. Subsequently, SVR was employed to train the prediction model.	NAM data
[33]	Short-term forecasting	GHI	In this study, three physical models were examined for predicting PV power generation using crystalline PV panels. A comparison was made among these models using real weather data.	Experimental data
[29]	Medium-term forecasting	CMV	In this study, wavelet analysis was utilized to examine decomposed components with scaled resolutions.	Sky images
[30]	Long-term forecasting	WVM	A Wavelet-Based Variability Model" is a model that analyzes variability in data sets using wavelet transformation and is widely used in the fields of time series analysis and signal processing.	--
[28]	Long-term forecasting	SVM FFA	In this study, the developed SVM-FFA model provided a distinct approach to predict solar radiation applicable to various climatic conditions.	Ground-based sky images
[34]	Long-term forecasting	CNN CSL	In this particular study, a novel approach was formulated to forecast the monthly mean daily solar radiation (GSR) for densely urbanized cities. This approach involved the construction of an Extreme Learning Machine (ELM) model that integrated various analytical datasets to enhance the accuracy of the predictions.	Satellite-derived data
[35]	Long-term forecasting	-	In this research study, several deep learning techniques were evaluated and compared to predict both hourly and daily solar radiation levels for a forecast period extending one year into the future.	US National Digital Forecast Database

3. FORECASTING BASED ON HISTORICAL DATA

Solar forecasting methodologies can be classified into different groups, as depicted in Figure 3. Typically, these forecasting approaches leverage historical meteorological data and various external variables as inputs for their prediction models [36]. Alternative approaches for estimating solar radiation and PV output utilize satellite imaging for data gathering [37].

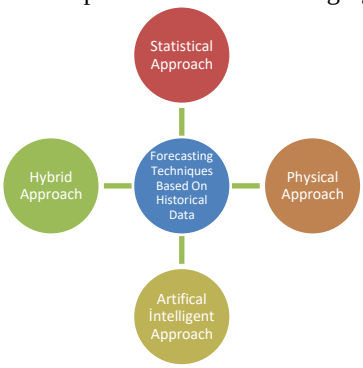


Figure 3. Forecasting techniques based on historical data.

3.1 Statistical Forecasting

Statistical techniques rely on the learning process of an estimation model using historically effective variables. Unlike other approaches, statistical forecasting does not require confidential system-generated information being modeled. The methodology is grounded in data analysis, drawing upon historical datasets to discern patterns and anticipate forthcoming patterns of a facility's performance. Hence, the precision of prognostications is significantly contingent upon the caliber of the historical data employed [5].

The primary objective of the forecasting model is to reduce network learning error by juxtaposing the predicted photovoltaic (PV) output power derived from the network against the real measured values. As a result, statistical models are built upon historical patterns. The predictive performance quality and historical input data length of a statistical model are directly proportional [12]. In practice, statistical learning methods are often used to correct errors in the outputs of NWP models and combine outputs from multiple models through a process known as model output statistics to enhance the accuracy of predictions. [38]. A summary of statistical estimation studies can be found in Table 3.

3.1.1 ARMA

The Autoregressive Moving Average (ARMA) model is regarded as a prominent technique in time series forecasting owing to its adeptness in encapsulating statistical characteristics [39]. When used in conjunction with stationary input variables, it is deemed a reliable model for predicting future values of time series [12]. The ARMA model theoretically consists of two fundamental components: autoregressive (AR) and moving average (MA) [40]. In the nomenclature of ARMA modeling, it is denoted as (p, q), with 'p' signifying the order of the autoregressive (AR) component and 'q' representing the order of the moving average (MA) component.

$$X = \sum_{i=1}^{p} \alpha_i X(t-i) + \sum_{j=1}^{q} \beta_j e(j-i) \quad (1)$$

where X(t) signifies the forecasted PV power, the values 'p' and 'q' signify the orders of the Autoregressive (AR) and Moving Average (MA) models, correspondingly. Within these models, αi and βi represent the respective coefficients. Meanwhile, e(t) symbolizes white noise, responsible for generating random and uncorrelated variables [41]. The ARMA model utilizes a set of equations to describe time series data at various orders, and it is especially well-suited for handling stationary time series data. Indeed, the ARMA model is most effective when applied to stationary time series data [42].

3.1.2 ARIMA

The Automatic Regression Integrated Moving Average (ARIMA) model finds extensive application in time series analysis and holds a widely acknowledged status as a reference method [43]. A primary limitation of the ARMA model is its demand for time series data to exhibit stationarity, which means that the statistical characteristics of the data must remain consistent over time. To mitigate this constraint, the ARIMA model was introduced specifically to address nonstationary random

processes. ARIMA processes are part of a category of stochastic processes employed for the analysis of time series data [44]. A model of ARIMA (p, d, q) for a nonstationary random process X_t can be formulated as follows:

$$\left(1 - \sum_{i=1}^{p} \varphi_i \, L^{i}\right) + \, (1 \, - \, L)^{d} \, x_t = \left(1 - \sum_{i=1}^{q} \theta_i L^{i}\right)\varepsilon_t \tag{2}$$

where L represents the lag operator defined by $L_{Xt} = Y_{t-1}$, φ_i is the AR coefficient, θ_i denotes the moving average (MA) coefficients, ε_t represents white noise consisting of independent and identically distributed random variables with a mean of zero, 'p' stands for the order of autoregression, *'d'* represents the number of nonseasonal differences, and *'q'* is the order of the moving average, ARIMA models exhibit remarkable flexibility. They can represent various types of time series, including pure autoregressive (AR), pure moving average (MA), and combined autoregressive and moving average (ARMA) series. However, it's important to note a significant limitation of ARIMA models: they assume a linear form, meaning they presuppose a linear correlation structure between time series values. Consequently, ARIMA models are unable to capture nonlinear relationships that might exist in the data [45].

3.1.3 ARMAX

Power systems exhibit nonlinear and dynamic behaviors in their load characteristics. Apart from seasonal and daily fluctuations, the load profile is frequently affected by environmental weather conditions. To precisely model the non-linear connection between the load and weather variables, the External Input Autoregressive Moving Average with Exogenous Variables (ARMAX) model has been employed [46]. In the context of solar radiation prediction, the inclusion of data pertaining to local temperature, relative humidity, cloud cover, wind speed, wind direction, and other pertinent factors can effectively mitigate the margin of error in the predictive model. These variables, while operating independently of the model itself, exert a significant influence on its outcomes and are denoted as exogenous variables [47]. Incorporating the external input term '*p*' enables the representation of the ARMAX (*m, n, p)* process as an extension of the ARMA (*m, n*) models [54-55-56-57].

Table 3. Studies based on statistical forecasting.

Ref	Model	Description
[48] [49] [50]	**ARIMA**	The generalization of ARMA modeling that incorporates differencing and can effectively manage nonstationary time series is often referred to as ARIMA modeling.
[51] [52] [53]	**SARIMA**	A model constructed by introducing supplementary seasonal components into ARIMA models is typically called a Seasonal ARIMA (SARIMA) model. These seasonal terms are integrated into the ARIMA framework to capture recurring patterns and trends in time series data that follow a specific seasonal pattern.
[54] [55] [56] [57]	**ARMAX**	The generalization of ARMA modeling that includes differencing is known as the Autoregressive Integrated Moving Average (ARIMA) model. It's designed to handle nonstationary time series data by differencing the series to make it stationary before applying ARMA modeling.

3. 2. Physical Forecasting

The physical approaches to PV power forecasting rely on mathematical models of PV arrays [58]. These approaches consider various factors such as the location and orientation of the PV plant, historical data, and meteorological variables. Physical forecasting models are constructed by considering the characteristics of photovoltaic systems alongside anticipated meteorological factors such as global horizontal irradiance (GHI), relative humidity, as well as wind speed and direction [12]. Local meteorological data is used to measure these weather variables, eliminating the need for surface solar radiation data. However, it is essential to note that these models require the conversion of digital numbers from radiometers into corresponding irradiance values, which necessitates the use of a suitable and regularly calibrated device [59]. The performance of the physical model in estimating PV power is higher when the weather conditions remain stable [60]. Table 4 provides an overview of the examination conducted on physical estimation methods.

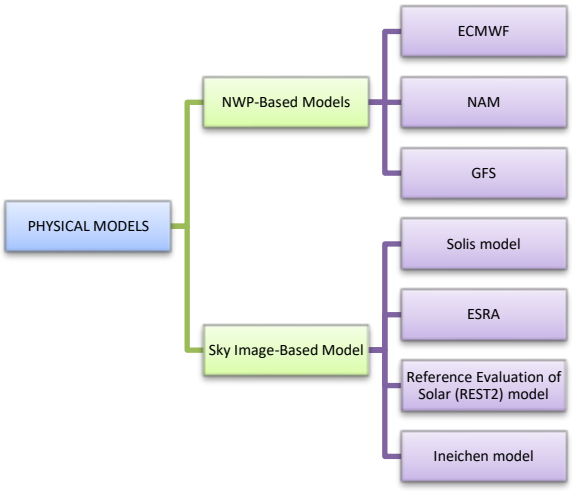


Figure 4. Physical models for solar forecasting.

3. 2.1 Numerical Weather Prediction (NWP)

Precisely predicting solar radiation holds paramount importance for the effective functioning of solar power facilities, energy market operations, and the widespread integration of PV technology [61]. NWP is often considered the most accurate tool for predicting solar radiation several hours in advance [62].

NWP models can be categorized into two main types: global and regional models. Global models simulate atmospheric conditions on a worldwide scale, whereas regional models concentrate on specific and limited geographic areas, such as continents, countries, or regions [63]. NWP models provide forecasts with temporal resolutions in hours and can predict up to several days ahead [81]. Satellite-based systems can achieve more precise forecasts, particularly up to 8-9 hours ahead [82]. However, it should be noted that satellite image models are suitable for shorter-term forecasts, typically ranging from 1 to 5 hours. In contrast, NWP models have the capability to predict the atmospheric state up to 15 days in advance [40]. The NWP models listed in Table 4 are spherical models with a relatively coarse resolution, making them insufficient for capturing intricate details of small-scale features. These models are created through numerical integration of interconnected differential equations that elucidate the transport of radiation and the dynamics of the atmosphere. One notable advantage of NWP models is their foundation on deterministic physical models.

By leveraging NWP models, solar radiation can be estimated by incorporating various atmospheric parameters, which allows for more accurate solar power forecasting and planning. These models play a vital role in optimizing the operation and integration of solar power plants into the electricity grid, contributing to the efficient utilization of renewable energy resources.

3. 2.2. Clear-Sky Models

Cloud cover indeed exerts a substantial influence on solar irradiance. Nevertheless, it is feasible to predict solar irradiance in the absence of clouds, under clear-sky conditions. Clear-sky models depend on precise measurements of aerosol optical depth, water vapor content, and ozone levels to make these predictions accurately [64]. These atmospheric parameters are generally not directly measurable at the specific location but are made available as gridded forecasts with relatively low spatial resolution, such as 1 degree. Clear-sky models employ meteorological variables and solar geometry in combination with radiative transfer models to establish relationships between these input parameters [5]. These models can then be used to derive solar radiation components by employing methods such as persistence estimates, normalization of predictive skill criteria, and normalization of satellite data [47]. Several clear-sky models have been developed, and Table 5 provides an overview of studies related to these models.

An illustration of such a model is the European Solar Radiation Atlas (ESRA), which applies the Bouguer-Lambert-Beer law and characterizes atmospheric transmittance by employing the Linke turbidity factor (TL). This model omits considerations for Rayleigh scattering [65]. Another model worth noting is the Solis model, which was developed as part of the European Heliosat-3 project in 2004. This model is characterized by its spectral resolution in clear-sky transmittance estimation. It leverages radiative transfer calculations along with the Lambert-Beer relation for its predictions [66]. The Ineichen model, named after its developer, provides an independent estimation of the Linke turbidity coefficient, irrespective of air mass [47].

These models differ in terms of the inputs they require. For instance, some models like ESRA and Ineichen rely on a single input, while others such as Solis incorporate multiple inputs to estimate clear-sky conditions. Each model offers its own advantages and may be suitable for specific applications based on availability of input data and desired level of accuracy.

Table 4. Studies based on physical forecasting.

Methods	Description	Data	Ref
Global Forecast System (GFS)	A global weather forecast model" is a global weather prediction model used to provide weather forecasts for various regions around the world.	Meteorological data	[67]
North American Mesoscale (NAM)	A regional weather forecasting model used by the National Centers for Environmental Prediction (NCEP)	Physical and historical data	[68]
NWP	Day-ahead solar forecasting exclusively performed using NWP	Physical data	[69]
NWP	Described a new approach to online forecasting of power production from PV systems.	Climatic and electrical data	[70]
Weather Research and Forecasting Model (WRF)	The Weather Research and Forecasting (WRF) model is employed, integrated, and coupled with a statistical post-processing technique to produce solar radiation forecasts for the northeastern region of Brazil.	ANFIS and NARX models	[71]
Coupled Auto Regressive and Dynamical System (CARDS)	Autoregressive (AR) and dynamical system (DS) models were coupled together	Historical power data	[72]

Table 5. Studies based on clear-sky models.

Methods	Descriptions	Ref
ESRA	A clear-sky irradiance model developed within the European Solar Radiation Atlas project. It estimates global, direct, and diffuse solar irradiance under cloud-free conditions using the Bouguer–Lambert–Beer law and the Linke turbidity factor to characterize atmospheric transmittance.	[65]
SOLİS	The researchers have created an updated version of the Solis model, which encompasses three key components: global, direct, and diffuse solar radiation. This improved version of the model is designed to work with four distinct aerosol types, as defined by Shettle and Fenn, and can handle turbidity values spanning up to 7.	[66], [73]
Ineichen	This model was developed to generate the Linke turbidity coefficient independent of the air mass	[66], [74], [75]

3.3. Artificial Intelligence (AI) Approach

Early studies on solar forecasting mainly relied on traditional statistical and physical approaches such as persistence models, ARIMA, and NWP-based methods. Although these approaches provided useful baseline predictions, they often struggled to capture complex nonlinear relationships in solar and meteorological data[104]. With the increasing availability of large datasets and computational power, artificial Intelligence (AI) methodologies assume a pivotal role across a spectrum of disciplines, encompassing control systems, predictive analytics, optimization processes, and the identification of patterns. Their profound proficiency in data analysis and regression renders AI techniques especially invaluable when it comes to modeling and forecasting solar energy [40]. Table 6 offers a comprehensive summary of forecasting models that harness AI techniques within the domain of solar energy. These models employ AI algorithms to scrutinize historical data, discern underlying patterns, and generate precise forecasts for solar energy production. The integration of AI into solar energy forecasting has made substantial strides in augmenting the effectiveness and dependability of solar power systems.

3. 3.1. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) have discovered utility across a wide array of domains, encompassing control systems, data compression, estimation processes, optimization tasks, pattern recognition, and classification procedures [76]. In the domain of solar energy forecasting (as depicted in Figure 5), ANNs are widely employed and recognized as a prominent machine learning technique [76].

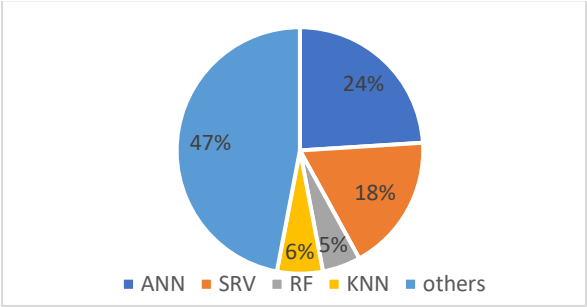


Figure 5. The categorization of research studies based on the machine learning technique employed.

Neural networks consist of interconnected neurons that process input variables and generate corresponding output signals [77]. Due to the nonlinear nature of meteorological data, researchers have extensively utilized ANNs for PV power generation estimation [17]. One notable advantage of ANN models over other nonlinear models is their ability to approximate a wide range of functions with high accuracy, making them universal approximators [78]. ANN models process information in parallel, leveraging the properties of the data to determine the network structure without assuming a specific model form in advance. The numerical weights assigned to the connections between neurons are adjusted during the training phase to achieve optimal prediction performance. This versatility has made ANN models valuable in various scenarios with diverse input variables.

3. 3.2. Support Vector Machine (SVM)

Support Vector Machines (SVM) were indeed formulated by Vladimir Vapnik as a classification algorithm [79]. SVM has gained popularity in recent years for both classification and regression analysis tasks [80]. SVMs are known for their strong problem-solving capabilities [5]. In the realm of time series regression, the utilization of Support Vector Machines is known as Support Vector Regression (SVR) [17]. In PV research, SVR is frequently applied to model input/output data associated with variables like temperature, precipitation probability, and solar radiation. SVR is a nonlinear regression algorithm designed for time series data analysis. One approach it employs involves mapping data to a high-dimensional feature space using non-linear mapping techniques and then conducting linear regression within that transformed space. Through the utilization of kernel functions, SVR demonstrates its capability to effectively capture intricate nonlinear relationships between input variables and the target variable, thereby facilitating precise predictions in time series regression tasks.

3. 3.3. K-Nearest Neighbor (KNN)

K-Nearest Neighbors (KNN) is a simple and widely used machine learning method for classification tasks in various applications [81]. The concept of KNN is straightforward, making it a popular choice for classification problems.

In KNN, each data point in each dataset is ranked based on its proximity to the training examples in the feature space. The algorithm utilizes a pattern recognition approach by comparing the current state with the training examples. This comparison is typically done using Euclidean distances between data points. The K nearest neighbors, where K is a user-defined parameter, are then selected for estimating or classifying the current data point [5].

In the context of solar energy forecasting, KNN can be applied to classify a forecast period based on historical periods with similar weather conditions [82]. By identifying the historical periods that closely resemble the current forecasted conditions, KNN can provide insights into the expected solar energy output for the forecasted period.

KNN's simplicity and ability to capture similarities between data points based on feature space proximity make it a useful tool for classification tasks and can be utilized in solar energy forecasting to leverage historical weather patterns for predicting solar energy generation.

3. 3.4. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a recurrent neural network architecture proposed by **Hochreiter and Schmidhuber** to capture and learn long-term dependencies in sequential data [105]. Unlike traditional neural networks, LSTM is capable of learning long-term dependencies in time series by using a memory cell structure and gating mechanisms that regulate the flow of information [106].

In solar energy forecasting, LSTM models are particularly suitable for capturing temporal variations in solar irradiance and photovoltaic (PV) power generation. By learning patterns from historical meteorological and solar generation data, LSTM can provide accurate short-term and day-ahead predictions of solar power output [107].

Table 6. Studies based on artificial intelligence (AI).

Ref	Method	Time Horizon	Parameter Used
[83]		12-h ahead	On-site measurement: solar irradiance modular temperature
[93]	**SVR**	Hour ahead	Performed using polynomial regression and Lasso.
[86]		5-h ahead	NWP measurement
[90]		Monthly/daily	Solar radiation in Turkey
[84]		24-h ahead	Weather data and historical measurement
[87]	**ANN**	1-3-12-24-h ahead	Ambiance temperature
[88]		N/A	Global horizontal irradiance
[31]	**KNN**	1-d ahead	Solar irradiance
[91]		Short-term	National electricity market (Australia)
[85]		N/A	Prediction of solar radiation
[92]	**SVM**	N/A	Cloudy weather condition
[89]	**RF**	N/A	Meteorological records and solar-computed values
[108]		Short-term	real-time meteorological variables such as AT, MT, H, WS, WD and GH
[109]	**GRU**	Very short-term	South Korea's national power system data from 2021 to 2023

4. HYBRID APPROACH

Hybrid forecasting models have gained popularity in solar energy estimation due to their ability to overcome limitations associated with individual models. These hybrid models represent a fusion of two or more statistical methodologies, referred to as hybrid statistical models, or they combine statistical approaches with PV performance models, known as hybrid physical models. This amalgamation empowers these models to provide more precise and reliable predictions.

Numerous research investigations have delved into the utilization of hybrid models for solar energy forecasting. For instance, in the study conducted by Pedro et al., a combination of weather report data, fuzzy theory, and a neural network was employed to forecast the power output of a PV system with a focus on predicting sunshine conditions 24 hours in advance [95]. Asrari at al. combined gradient descent optimization and metaheuristic optimization methods to achieve enhanced prediction accuracy. [9]. Zhang et al. introduced a hybrid approach for PV power forecasting. Their method combines a SARIMA model with an ANN. They incorporate weighing factors that are computed periodically through a least squares problem as part of their hybrid forecasting technique [96]. This approach facilitates short-term forecasts covering time horizons spanning from 15 minutes to a day or even longer, rendering it well-suited for applications like Model Predictive Control (MPC). Cortes and Vapnik introduced a hybrid weather-dependent approach designed for forecasting hourly PV power output one day ahead. Their method incorporates classification, training, and estimation steps in the forecasting process [97]. Sharma et al. applied a predictive approach that integrates a Long Short-Term Memory (LSTM) neural network along with a K-means algorithm. This method is employed for forecasting PV power generation by leveraging historical radiation data, which accounts for dynamic sky types that vary from hour to hour during the same season [98]. Denoeux et al. introduced an innovative model for ultra-short-term prediction of solar PV generation. This model relies on deep full-sky image learning architectures and employs hybrid methods that merge NWP, SVM, and Hidden Markov Models (HMM) to enhance its predictive accuracy [99]. Wang et al. explored the effect of solar PV power time series on prediction using wavelet decomposition with SARIMA and RVFL models [100]. Reforecasting techniques utilizing optimization schemes with ANNs were applied to enhance the accuracy of three fundamental estimation models. These models include a deterministic physical model grounded in cloud tracking methods, an ARMA model, and a KNN model. [101]. Lew and Piwko used ARIMA and

KNN to train various forecast models for hourly average power output 1 and 2 hours ahead using data before January 2011 [77]. Garud et al. conducted a study to assess the appropriateness and dependability of several modeling approaches, including ANN, Functional Link (FL), Genetic Algorithm (GA), and hybrid models. Their aim was to achieve precise estimates of solar radiation and evaluate the performance parameters of solar PV systems. Thomas Haupt et al. prepared a novel hybrid framework was developed by amalgamating time series state space models and AI-driven methods. This integration aims to enhance the forecasting accuracy of PV systems, achieving an error rate of approximately 3% nRMSE across various orientations [102]. Wan et al. developed an integrated predictive model combining BiGRU and TCN with a self-attention mechanism. Their approach employs a hybrid MSADBO algorithm for automated hyperparameter optimization, achieving superior performance under abrupt power fluctuations compared to traditional deep learning baselines. [103]. These hybrid forecasting models leverage the strengths of multiple approaches, combining statistical and physical models or machine learning techniques to increase the accuracy and reliability of solar energy estimation and forecasting.

5. CONCLUSION

Solar energy forecasting plays a crucial role in the energy markets, and reliable estimates are essential. Uncertainty in solar resource assessment poses challenges in obtaining accurate forecasts. Different techniques are utilized for different climatic conditions and time horizons to address this challenge.

Research in the field of solar energy forecasting can be categorized according to forecast horizons and the type of historical data utilized. Day-ahead forecasts are particularly crucial, as energy markets operate across various time zones, with most energy trading occurring in day-ahead markets. Studies based on historical data employ statistical, physical, machine learning, or hybrid methods to estimate solar energy levels. Each of these methods comes with its unique advantages, which are comprehensively elaborated.

ANN and SVM are frequently employed techniques due to their capability to handle intricate and nonlinear prediction models effectively. However, recent research has exposed the constraints of relying on isolated forecasting models. This shift has catalyzed a preference for hybrid frameworks that integrate multiple methodologies. The fundamental objective of these composite systems is to refine the precision of solar output estimations by leveraging the synergistic attributes of diverse modeling paradigms.

Anticipated advancements in AI algorithms, particularly in the domains of machine learning and deep learning, hold the potential to significantly enhance PV forecasting systems in the near future. These cutting-edge technologies are technologies are set to bolster the dependability of solar predictions. By providing more rigorous data insights, they allow power producers to streamline their processes and maximize profitability. The use of AI technologies also improves data analysis and forecasting model development, leading to optimized and sustainable solar energy production.

In conclusion, with the development and adoption of PV power prediction systems, driven by advancements in solar energy production and AI technologies, solar energy producers can operate more efficiently and sustainably. These systems contribute to the overall growth of the solar energy sector and help optimize solar energy production in the future.

Authors' Contributions

In this study, authors contributed equally to the study.

Competing Interests

The authors declare that they have no conflict of interest.

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