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SURVEY

Illuminating the Future: A Comprehensive Review of AI-Based Solar Irradiance Prediction Models

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ABSTRACT Meeting the energy needs of a growing population is of paramount importance in today's society. The use of renewable energy sources, especially solar energy, can help reduce greenhouse gas emissions from traditional sources. Solar irradiance, which depends on several factors such as the availability of sunlight, cloud cover index, latitude, orientation and tilt of solar panels, and technical factors, plays a crucial role in the use of solar energy. Predicting solar irradiance is therefore essential for enhancing the reliability and efficiency of solar energy systems. Artificial intelligence (AI) and machine learning (ML) models are increasingly being used to predict solar irradiance forecasting. These models can learn from historical weather data and identify complex patterns to predict future solar irradiance with high accuracy. Techniques such as regression, neural networks and ensemble methods are frequently used and enable more efficient planning and operation of solar energy systems. This study provides a comprehensive analysis of the existing state-of-the-art models for solar irradiance forecasting. The study evaluates a variety of forecasting models, including machine learning, numerical weather prediction and hybrid approaches for assessing their accuracy, strengths and weaknesses. As an outcome of this study, potential future improvements in the prediction of solar irradiance are highlighted and the importance of interdisciplinary collaboration and emerging technologies is emphasized. To ensure a sustainable and resilient energy future, it is crucial to continue efforts to better integrate solar energy into mainstream electricity systems. This work can serve as a fundamental analysis for future researchers to identify the most appropriate approaches for medium and long-term solar irradiance forecasts.

INDEX TERMS Artificial intelligence, renewable energy, solar irradiance, machine learning, forecasting.

I. INTRODUCTION

Conventional energy sources are not sustainable and have a negative impact on the environment, research into alternative energy sources has recently gained popularity. In addition, there is a growing global energy crisis, as economic and technological progress is highly dependent on the availability of energy, which is necessary for global industrialization and urbanization. On the other hand, increasing global population growth has lead to the energy shortage in the world. The consumption of fossil fuels increases with the demand for energy. Fossil fuels such as coal, natural gas and oil are used to produce brown energy, which is harmful to the environment and more expensive. Solar energy is abundant and cheap renewable energy source (RES). Carbon emission rate of green energy is lower than that of brown energy [1]. In case of

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conventional power plants, considering the long term impacts of carbon emissions, the countries imposed high taxes on carbon emission [2], [3].

Policy makers and researchers face significant challenges in deciding how to reduce electricity costs and ensure environmental sustainability. The research community has been working on an enormous green energy solutions [4], [5], [6]. Recent research trends indicate that the most cost-effective and environmentally friendly way to meet human energy needs is to combine green energy with brown energy sources [7], [8], [9]. Solar and wind energy are the most common types of green energy that can be used. However, the volatile weather conditions affect the production of solar and wind energy differently.

Generation of solar energy is intermittent with the naturally available solar irradiance and it is influenced by meteorological factors in different time zones [10], [11], [12]. Due to its intermittent nature, the integration of solar energy into the current energy system is a significant challenge despite its seemingly low cost [13]. Main challenge of intermittency is more prominent when solar energy is the only power source. Therefore, the literature recommends utilising the renewable energy sources along with brown energy sources. Unreliable meteorological factors such as availability of solar irradiance, time of day and season, cloud cover index, latitude, orientation and tilt of solar panels can affect solar power generation [14], [15]. To reduce carbon emissions, control grid operating costs, ensure safe grid management, balance electricity demand and supply, and plan power generation to improve the utilisation of reserves, accurate forecasting of solar power generation is critical [16], [17].

Growth of a country depends on the important role of cost-effective power generation [18] and zero-carbon electricity generation is possible with solar energy [19], [20]. Many artificial intelligence (AI) based methods namely: neural network (NN), support vector regression (SVR), long short-term memory (LSTM), gated recurrent unit (GRU), convolutional neural network (CNN) and multi-layer perceptron (MLP) are proposed by the research community for solar irradiance prediction [21]. More recently, hybrid methods such as extreme gradient boosting tree (XGBT) and deep neural networks (DNN) have been used to predict hourly irradiance [22]. Since PV generation depends on the nature of solar radiation, the operation of the power grid is complicated [23]. A DNN model is proposed by the authors of [24] to predict irradiance within one day using a deep learning (DL) model without the need for real-time data measurement.

The need for low-cost solar energy, which is readily available in the form of abundant global horizontal irradiance (GHI), is an essential requirement in today's industries. [25]. The GHI data of solar irradiance depends on the horizon and meteorological parameters [26]. GHI-based models may be classified as image-based, empirical methods, statistical and learning models [27], [28]. In recent past, meteorologists employs solar irradiance information for the prediction of solar energy predictions [29], [30].

In this systematic literature review, we formulate three major research questions and perform the survey of existing literature to answer these research questions. The formulated research questions (RQs) are given in the following.

1) RQ 1: What are the key research challenges identified in existing review articles regarding AI-based solar irradiance prediction models?
2) RQ 2: What common tools, techniques and models are used in modern research to predict solar energy? What challenges does the research community face?
3) RQ 3: What are the emerging trends and future directions in AI-based solar irradiance prediction research.

Based on these research questions, main contributions of the study are given in the following.

1) The paper presents a comprehensive and systematic review of existing literature (both review articles and state-of-the-art research) along with SWOT analysis, providing insights into the current status and challenges of AI-based solar irradiance prediction models
2) By synthesizing findings from previous reviews and research articles, this paper identifies research challenges in current knowledge and understanding within the field
3) Through a critical analysis of methodologies employed in reviewed articles, this paper evaluates the efficacy and applicability of various tools, techniques, and models utilized in solar energy forecasting
4) Identified challenges for future research challenges of AI-based solar irradiance prediction

The rest of the work is organized as follows. Preliminary remarks and background information to assist new readers are described in Section II, while the current state of the literature is presented in Section III. The research methodology is described in Section IV. Strengths, weaknesses, opportunities and threats (SWOT) analysis of the AI-based solar irradiance prediction models is given in Section V. The research challenges solar irradiance prediction are discussed in Section VI and the key finding of this study are summarized in Section VII. Finally, Section VIII concludes this study with future work.

II. PRELIMINARIES AND BACKGROUND

A section of preliminaries and background information is included in the study to provide a solid foundation to the readers of solar irradiance prediction domain. List of frequently used abbreviations in this study is shown in Table 1.

A. SOLAR FORECASTING HORIZONS

The time interval in the future for which a forecast is required is called the forecast horizon. Four categories are commonly used to classify solar forecast horizons: very short-term, short-term, medium-term, and long-term. To date, there is no uniform classification system for forecast horizons. Depending on the type of prediction horizon, solar irradiance prediction can be used for various applications for the successful and efficient operation of PV power plants.

1) VERY SHORT-TERM SOLAR FORECASTING

The term very short-term forecasting usually refers to predictions about trends or events that will occur in the next few second, minutes or hours [31]. This is essential for real-time decision-making. Very short term solar forecasting applications use state-of-the-art algorithms and real-time data to predict the near future solar energy generation with extreme accuracy, allowing for quick adjustments and better planning. Predicting very short-term solar irradiance is useful for peak load balancing, real-time power grid monitoring, bidding, and electricity pricing [32].

2) SHORT-TERM SOLAR FORECASTING

An essential component of effective solar generation management is short-term solar forecasting, i.e., predicting the amount of solar electricity that will be generated in the next few hours or days [33]. Grid operators, utilities, and solar power plant operators rely on this type of forecasting to balance supply and demand in real time, unit commitment, bulk energy storage, planning in electricity market and ensure stability of the electric grid [34]. To predict how much energy solar panels will produce, short-term solar forecasting uses sophisticated algorithms, solar irradiance models and weather data. Accurate predictions facilitate the injection of solar energy into the power grid and reduce dependence on non-renewable energy sources during periods of maximum solar output.

3) MEDIUM-TERM SOLAR FORECASTING

Forecasting solar energy generation over a period of weeks or several months is called medium-term solar forecasting [35]. It is useful for resource allocation, grid management, grid maintenance and energy planning. This type of forecast provides a fairly accurate estimate of solar power generation by taking into account variables such as seasonal variations, cloud cover patterns, and historical data. To optimize power generation and distribution plans, make informed investment decisions, and improve energy sustainability on a larger scale, medium-term solar forecasts are useful for energy markets, utilities, and policy makers.

4) LONG TERM SOLAR FORECASTING

Long-term solar forecasting is about predicting solar energy generation over extended periods of time, often several months to years in advance [36]. This type of forecast is critical for strategic energy planning, infrastructure development, and investment decisions. Long-term solar forecasts take into account factors such as climate patterns, geographic location, and the potential for technological advances in the solar energy sector. These forecasts are particularly valuable to renewable energy initiatives, large-scale solar projects, and policymakers, as they help them make informed decisions about the long-term integration of solar into the energy landscape and the sustainable energy transition [37]. Graphical presentation of solar forecasting horizons, time steps and respective application areas are shown in Figure 1.

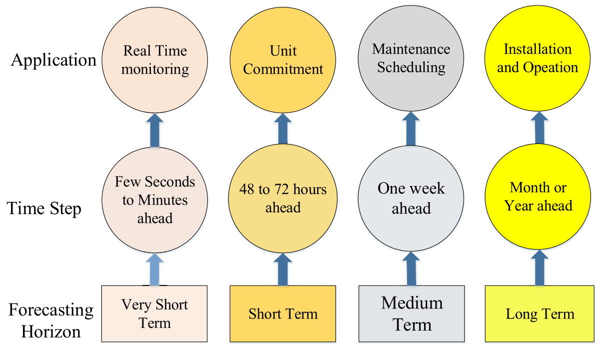

FIGURE 1. Solar irradiance forecasting horizons, time steps and respective application areas.

B. PERFORMANCE METRICS

The research community has done much to provide mankind with accurate and reliable solar irradiance prediction models. The performance of these prediction models is compared based on performance metrics. Some important and popular performance metrics are discussed in the following subsections.

1) MEAN ABSOLUTE ERROR (MAE)

The average absolute differences between predicted and actual values in a data set are measured by the mean absolute error (MAE) [38]. It is a useful metric for evaluating the accuracy of a predictive model because it quantifies the average magnitude of the errors in the model. Formula for calculation of MAE is given in following Equation 1, where x_i represents the forecasted i^{th} value, y_i denotes actual i^{th} value and n indicates # of iterations/forecasts.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \tag{1}$$

2) MEAN SQUARED ERROR (MSE)

Mean squared error (MSE) is a measure of the average of squared differences between actual values and predicted values in a data set. It quantifies the average magnitude of the squared errors in a predictive model and is often used in regression analysis as a measure of the accuracy of the model [39]. Formula for calculation of MSE is given in following Equation 2.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \tag{2}$$

TABLE 1. List of abbreviations.

Acronym	Description	Acronym	Description
AI	Artificial intelligence	AE	Auto-encoder
ANFIS	Adaptive neuro-fuzzy inference system	Bi-RNN	Bidirectional recurrent neural network
CSO	Chicken swarm optimization algorithm	CNN	Convolutional neural network
DNN	Deep neural network	DL	Deep learning
DBN	Deep belief network	ESN	Echo state network
FFNN	Feed-forward neural network	GBT	Gradient boosting tree
GAN	Generalized adversarial network	GRU	Gated recurrent unit
GWO	Grey wolf optimization algorithm	GHI	Global horizontal irradiance
LSTM	Long short-term memory	MLP	Multi-layer perceptron
MAE	Mean absolute error	MSE	Mean squared error
MAPE	Mean absolute percentage error	NN	Neural network
ML	Machine learning	PVPF	PV power forecasting
PV	Photovoltaic	RBF	Radial basis function
RES	Renewable energy source	RBM	Restricted boltzmann machine
RMSE	Root mean squared error	RNN	Recurrent neural network
RQs	Research questions	SVR	Support vector regression
SWOT	Strengths, weaknesses, opportunities and threats	XGBT	Extreme gradient boosting tree

3) MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)

An important performance indicator for assessing the accuracy of forecasting models is the mean absolute percentage error (MAPE). It calculates the typical percentage difference between the actual and predicted values of a data set. For applications where knowledge of the magnitude of the relative errors is critical, MAPE provides insightful information about the overall accuracy of a prediction model [40]. Formula for calculation of MAPE is given in following Equation 3.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - x_i|}{y_i}.100 \tag{3}$$

4) ROOT MEAN SQUARED ERROR (RMSE)

The square root of the average of the squared differences between the actual and predicted values in a data set is called the root mean squared error (RMSE) [41]. It gives an indication of the average size of the errors in a predictive model and is often used in regression analysis to assess the accuracy of the model. Formula for calculation of RMSE is given in following Equation 4.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{4}$$

5) CORRELATION COEFFICIENT (R)

The correlation coefficient (R) is a statistical measure that quantifies the strength and direction of the linear relationship between two variables. It ranges from -1 to 1, where -1 indicates perfect negative correlation, 1 indicates perfect positive correlation, and 0 indicates no linear correlation [42]. Formula for calculation of R is given in following Equation 5, where x_i represents i^{th} value of the x-variable, $\bar{x}$ indicates mean of the values of the x-variable, y_i represents i^{th} value of the y-variable and $\bar{y}$ indicates mean of the values of the x-variable.

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5}$$

6) SKILL SCORE (SS)

The Skill Score is an important performance metric for evaluating the precision and dependability of forecast models [38]. By comparing model's forecasted values to the observed or measured values, the skill score assesses how well it performs. Stakeholders in solar energy can assess forecasting algorithms' performance and pinpoint areas of strength and weakness in terms of prediction accuracy by using the skill score. Moreover, it can help improve forecasting models, energy production strategies, and the integration of solar power into the larger energy landscape. Formula for calculation of SS is given in following Equation 6 where A, represents accuracy of the proposed forecast model, $A_{reference}$ depicts accuracy of reference/standard forecast model and $A_{perfect}$ indicates accuracy of the perfect forecast model. $SS = 1$ indicates a perfect forecast whereas $SS < 0$ shows that prediction model is less accurate than reference forecast model and $SS > 0$ shows that prediction model is more accurate than the reference forecast model.

$$SS = \frac{A - A_{reference}}{A_{perfect} - A_{reference}} \tag{6}$$

C. MACHINE LEARNING MODELS

In this subsection, several well-known machine learning models used for solar irradiance prediction are briefly described to provide background knowledge for both beginners and experts in the field.

1) CONVOLUTIONAL NEURAL NETWORK

An artificial neural network specifically made for processing and evaluating visual data, such as images and video, is called a convolutional neural network (CNN). It has transformed the field of image identification and is extensively utilized

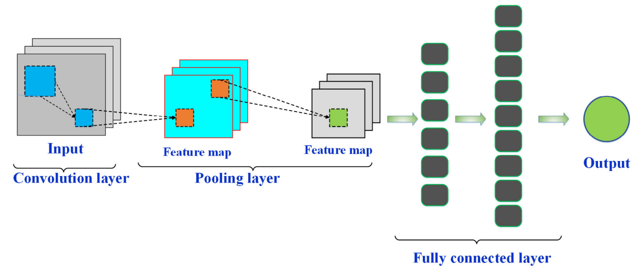

FIGURE 2. Convolutional neural network [43].

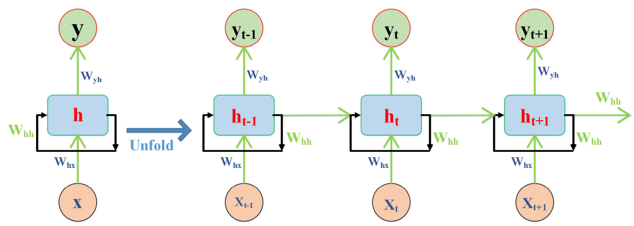

FIGURE 3. Recurrent neural network [44].

in computer vision jobs. CNNs are distinguished by their distinct design, which consists of fully connected layers for prediction, pooling layers for downsampling, and convolutional layers that automatically learn and detect patterns in the input data [3], [43]. Because CNNs can recognize hierarchical patterns and spatial correlations in the data, they have shown to be very effective in tasks like object detection, facial recognition, and image categorization. Technological advancements have made it possible for innovations in a number of fields, such as autonomous vehicles, healthcare, forecasting. A typical architecture of CNN is shown in Figure 2.

2) RECURRENT NEURAL NETWORK (RNN)

A type of artificial neural network designed to process sequences of data is the recurrent neural network (RNN). Because RNNs, unlike feedforward networks, are constructed with loops that allow them to retain a kind of memory, they are particularly well suited for applications that require sequential input, such as time series analysis, speech recognition, and natural language processing [44]. When processing new data points, RNNs consider previous inputs and decisions to capture temporal dependencies. However, they are limited in their ability to capture long-term dependencies by the vanishing gradient problem. Basic structure of RNN is shown in Figure 3.

3) DEEP BELIEF NETWORK (DBN)

Multiple layers of interconnected neurons form an artificial neural network, the deep belief network (DBN), shown in Figure 4. The architecture of DBNs combines discriminative and generative modeling, which makes them unique. Restricted boltzmann machines (RBMs) are stacked to create DBNs, with each layer using the data to learn and represent

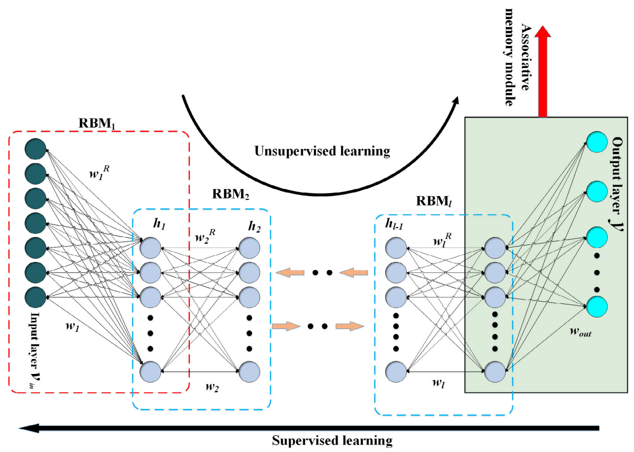

FIGURE 4. Deep belief network [45].

abstract attributes. They perform exceptionally well on unsupervised learning tasks such as feature learning, data representation, and dimensionality reduction [45]. DBNs are used in many domains, such as natural language processing, image processing, and speech recognition. Deep learning has benefited greatly from their ability to capture complicated hierarchical data representations.

4) GATED RECURRENT UNIT (GRU)

A recurrent neural network variant called gated recurrent unit (GRU) was created to overcome the difficulties in efficiently capturing long-range dependencies in sequential inputs while maintaining computational efficiency. Similar to LSTMs, GRUs use gating methods to regulate the flow of information, enabling them to sequentially store and update relevant context. GRUs are unique in that they have a simpler architecture with fewer gating units, which speeds training and often requires fewer parameters [46]. As a useful replacement for traditional RNNs and LSTMs, GRUs have become increasingly popular in natural language processing and other time series applications because they provide a reasonable balance between computational efficiency and performance. Basic structure of GRU is shown in Figure 5.

5) LONG SHORT-TERM MEMORY (LSTM)

Long short-term memory (LSTM) is a recurrent neural network architecture specifically designed to overcome the vanishing gradient problem that can hinder the learning of long-range dependencies in sequences. LSTMs have become a fundamental building block of deep learning for sequential data, such as natural language processing and time series analysis. They excel at capturing and storing information over long periods of time, as they can selectively update and forget information through special gating mechanisms [47]. This makes LSTMs well suited for tasks such as language modeling, machine translation, and speech recognition, where understanding context and relationships over time is critical. LSTMs have significantly advanced the field of deep

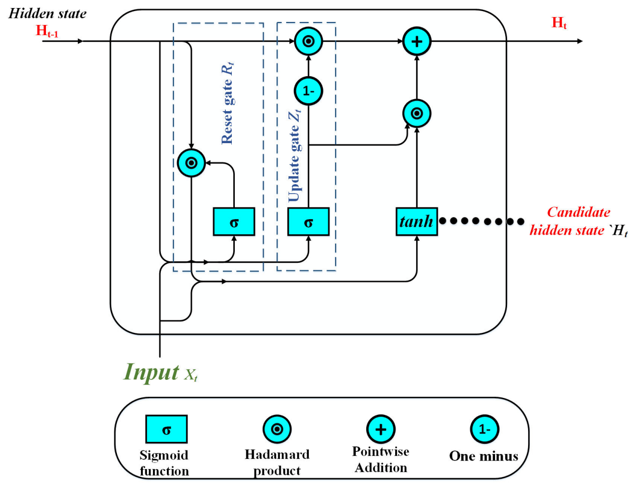

FIGURE 5. Gated recurrent unit [46].

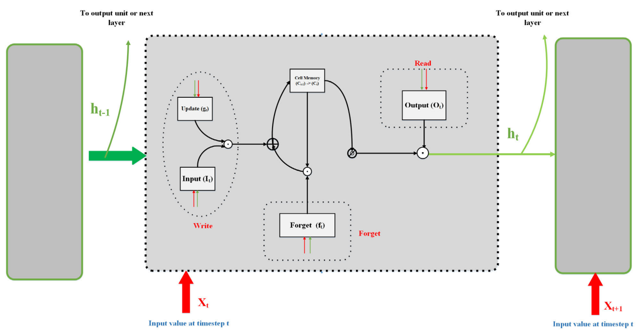

FIGURE 6. Long short-term memory [47].

learning and remain an important component in many modern sequential data processing models. Information processing in LSTM is shown in Figure 6.

6) BIDIRECTIONAL RECURRENT NEURAL NETWORK

A bidirectional recurrent neural network (Bi-RNN), shown in Figure 7, is a type of neural network architecture designed to capture information from both past and future data points in a sequence. This is accomplished by processing the input sequence in two directions: forward and backward. This dual processing allows the network to effectively learn from the context that precedes and follows each data point, making Bi-RNNs particularly useful for tasks that require a thorough understanding of sequence data, such as natural language processing and speech recognition [48]. By combining information from both directions, Bi-RNNs can capture complex dependencies and are very useful for tasks such as sentiment analysis, named-entity recognition, and machine translation, where context plays a crucial role.

7) ECHO STATE NETWORK (ESN)

An echo state network (ESN) is a type of recurrent neural network known for its simplicity and efficiency in processing sequential data. ESNs consist of three layers: an input layer,

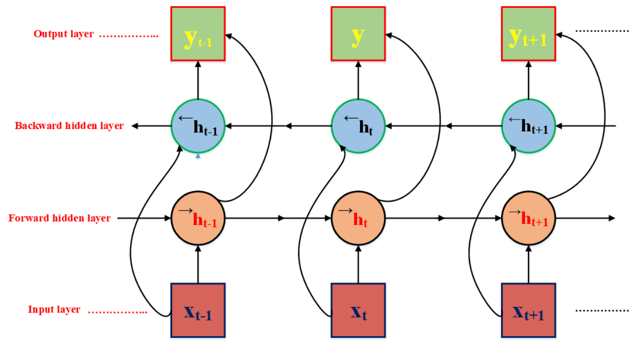

FIGURE 7. Bidirectional recurrent neural network [48].

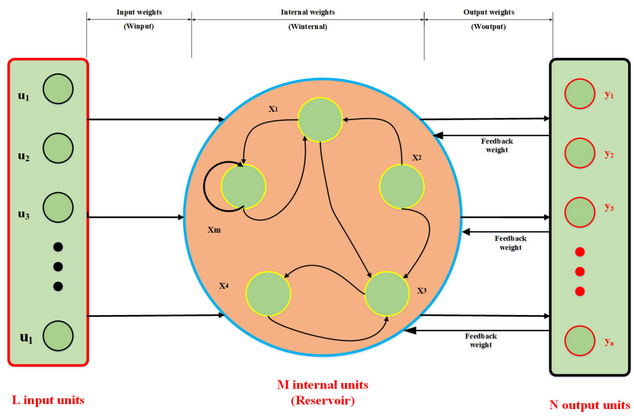

FIGURE 8. Echo state network [49].

a hidden layer, and an output layer. The unique feature of ESN is that the recurrent connections in the hidden layer are randomly generated and fixed, forming what is called a "reservoir". The dynamics of this reservoir can amplify and propagate input signals, which can then be trained to produce the desired output patterns [49]. ESNs are particularly suited to tasks such as time series prediction, speech recognition, and control systems. Their random and fixed structure enables a fast training process and makes them robust to overfitting. ESN shown in Figure 8 is a valuable tool in machine learning for various sequential data tasks.

8) GENERALIZED ADVERSARIAL NETWORKS (GAN)

Generalized adversarial networks (GANs), shown in Figure 9, often referred to as GANs, are a revolutionary class of artificial intelligence models used in generative tasks. GANs consist of two neural networks, a generator and a discriminator, that play a minimax game. The generator generates data, such as images or text, and the discriminator evaluates their authenticity. Through iterative training, the generator learns to generate increasingly realistic data, while the discriminator gets better at distinguishing real from generated data [50]. GANs have helped generate lifelike images, create deepfake videos, and improve various creative applications. They have also raised concerns about ethical and security issues, as they can potentially generate

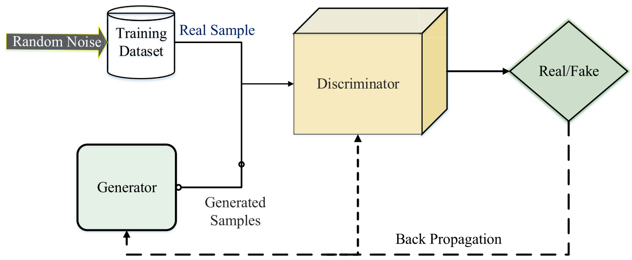

FIGURE 9. Generative adversarial network [50].

fraudulent content. Despite these challenges, GANs have opened new frontiers in machine learning and generative modeling, with numerous applications in art, entertainment, and even scientific research.

D. ADVANTAGES OF AI MODELS

Having discussed the machine learning models, it seems appropriate to mention the general advantages of AI models for solar irradiance prediction. Table 2 presents the main advantages of AI models for solar irradiance prediction.

III. LITERATURE REVIEW

This section presents a comprehensive review of the domain. we organize this section in two subsections, firstly, we provide a review of existing surveys followed by the a comprehensive review of existing literature.

A. EXISTING SURVEYS ON SOLAR IRRADIANCE FORECASTING

The research [51] reviews ML techniques for predicting the day lighting performance of buildings, their scope, algorithms, data sources, sizes, and evaluation criteria. The study investigates research parameters of previous research, including external climate, temporal settings, obstructions, building characteristics, openings and shading devices, occupancy and sensor data. Regression, decision trees and random forest are other common machine learning methods used to predict building performance, including daylight utilization. The study also addresses research gaps and opportunities for future innovations for architectural practice.

Yan et.al., [52] reviews forecasting models for renewable energy and electricity for energy planning and energy management. It reviews the wind energy forecasting, solar and geothermal energy as well as electricity load demand for short, medium and long time periods. ANN, ML and ensemble-based models are analyzed for their policy and planning relevance, accuracy and applicability. Furthermore, the research also analyzes the prediction of geothermal energy demand and the potential increase in installed EGS capacity by 2025, with a focus on predictive models for sustainable electricity demand and renewable energy management.

The authors of the paper [53] present an overview of ML models for predicting renewable energies. The study deals with the pre-processing of data, the selection of parameters and the measurement of predictive performance in such models. The study determines the mean absolute percentage error and the coefficient of determination for renewable energy sources. The paper [53] highlights the increasing popularity of AI and hybrid models to estimate solar and wind energy.

The study [54] gives an overview of applications of ML in predicting the energy performance of urban buildings from 2015-2018. The literature is categorized by learning method, building type, energy type, input data and time scale. Few studies have examined urban energy performance predictions and the impact of climate change on buildings. The stud concludes that no combination of criteria guarantees reliable predictions based on machine learning.

Due to the non-stationary behavior and changing atmospheric conditions, stand-alone forecast models are inadequate [55]. Hybrid models can improve forecast accuracy and overcome limitations [55]. The article [55] examines hybrid models and identifies interesting models. Due to differences in data and climate, it is difficult to evaluate the performance of hybrid models. The work provides initial guidance for hybrid models and tools to improve the assessment of solar irradiance.

The paper [56] presents a taxonomy of AI-based solar power forecasting models to increase prediction accuracy and select the optimum model for each application situation. It compares three AI-based deterministic solar power forecasting systems and their advantages and disadvantages. It also emphasizes selecting the appropriate AI optimizer to optimize the structure and parameters of the prediction.

Deep learning-based forecasting systems for wind and solar energy are reviewed in [57]. The review includes papers published between 2016-2020 on deterministic, probabilistic, deep learning architectures and hybrid models. The authors also discuss issues related to deep learning-based solar and wind energy forecasting and future research. A complete taxonomy of deep learning-based prediction research is proposed to accelerate innovation. The paper concludes with an outlook on future directions.

Methods for predicting wind turbines, solar panels and electrical load based on DL are discussed in detail in this study [58]. The study includes training and test datasets for DL-based forecasting models. DL forecasting requires historical data, which requires extensive data storage and powerful processing systems. The article identifies research gaps in renewable energy forecasting and the potential for smart microgrids.

The research [59] reviews DL-based PV power forecasting (PVPF) systems and highlights their advantages and disadvantages. It examines how PVPF and DL techniques can complement each other. Current algorithms for automatic architecture optimization for DL-based PVPF and DL technologies such as federated learning, deep transfer learning, incremental learning and DL for big data are also examined. The report present a taxonomy of DL algorithms for deterministic and probabilistic PVPF and concludes with

TABLE 2. Advantages of AI models.

Advantage	Description
Potential for Innovation	Artificial intelligence driven research into predicting solar irradiance creates new opportunities for creativity and the development of original methods and strategies.
Improved Forecasting	By combining a variety of data sources and adapting to changing environmental conditions, AI models can make more accurate and reliable predictions.
Reduced Dependency	By reducing the need for human intervention and expertise, AI models can improve the accessibility of solar irradiance predictions to a wider group of users.
Scalability	AI models can handle very large and diverse datasets efficiently, enabling effective utilization of diverse data sources for more robust predictions.
Adaptability	Through iterative learning processes, AI models are able to constantly improve their performance over time and adapt to changing environments.
Enhanced Accuracy	Since AI-based models can recognize complicated patterns and correlations in data, they are often more accurate than conventional techniques.
Handling Complex Data	Data types as diverse and complicated as satellite images, meteorological information and historical measurements of solar irradiance can all be processed by AI algorithms.
Real-Time Prediction	AI-based approaches are capable of generating real-time predictions, which is crucial for applications requiring timely and dynamic decision-making.

research gaps and future challenges for the success of PVPF DL. Auto-encoders (AEs), restricted boltzmann machines (RBMs), deep belief networks (DBNs) and generative adversarial networks are discussed. DL models predict PV better than others, but only at similar PV locations. DL has become increasingly popular in recent years, and the study emphasizes the need to utilize DL trends in predicting applications, especially for PV systems.

Hybrid learning methods using different methods can improve accuracy and prediction [60]. The authors of the review article [60] proposed to continue research in the field of hybrid learning in renewable energy generation. The study provides mathematical formulas for wind, solar and photovoltaic energy systems. DL and ML Models as well as optimization strategies are defined, described and analyzed in the paper [60]. The main objective of the review is to classify recent and notable research in the field of wind and solar energy using DL and ML.

The review paper [61] presents a comparison of 24 machine learning models for day-ahead electricity forecasting using NWP for 16 PV plants in Hungary. This study investigates how the selection of predictors and the adjustment of hyper parameters affect the forecast accuracy. The efficiency of ML with limited data availability is demonstrated using electricity forecasts that use the average daily irradiation forecasts and solar elevation angles. Optimizing model performance requires adjustment of hyper parameters, especially for less robust models.

Huang el.al., [62] provides a comprehensive overview of neural network models and ML approaches used to predict photovoltaic performance. While short and medium-term forecasts tend to have higher accuracy, the accuracy of longer-term forecasts tends to decrease. Climate change and weather classification affect the performance of forecasting models; these factors should be taken into account when making forecasts. RNNs and LSTMs are used to forecast photovoltaic output. The study addresses the input parameters of the prediction model, the resolution of the time steps and the length of the training and test data. MIM, RMSE and MAE are used to evaluate the forecasting models.

We present the summery of review articles on solar irradiance forecasting in Table 3. Table 3 revels that solar irradiance forecasting is an active research area and several researchers have reviewed the existing techniques of the domain. The exiting review articles also highlight several research challenges being faced. The identified research challenges include accuracy variations in different models, integration of forecasting with wind energy for enhanced power network usage, and need for the development of more precise models using transfer learning for the forecasting of renewable energy sources.

B. EXISTING LITERATURE ON SOLAR IRRADIANCE FORECASTING

Given the importance of solar energy and the environmental impact caused by the overuse of brown energy derived from fossil fuels, the research community has proposed numerous solar irradiance prediction models to stabilize the power grid. The current state of the literature on solar irradiance prediction is briefly described below.

A short-term prediction of solar radiation based on ML methods, HMM techniques and SVM regression is proposed by the authors of [30]. Simulation results confirm that the prediction algorithms based on ML can accurately predict the solar irradiance under different weather conditions. This study also discusses the general pattern of solar irradiance that repeats over the course of a day and the correct irradiance gradient at any given time, which can be used to predict future irradiance.

The development and use of the UTSA SkyImager is described in [63]. The original design of the SkyImager was used in the study to predict the cloud location, and ray tracing was used to predict the cloud location where shadows would fall on the solar panels. The study also describes an alternative strategy using AI to predict irradiance directly from a partial image extracted from the sun. Results and error metrics are

TABLE 3. Existing survey papers on solar irradiance forecasting.

Ref.	Year	Surveyed techniques	Research challenges	Targeted Energy
[51]	2020	• Several AI models	• Accuracy variation in different models	• Solar energy
[52]	2020	• AI models • Monte Carlo simulations • ARIMA • Radial function • Ensemble models	• Integrating forecasting wind energy usage into power networks • Prediction of solar radiation methods for different forecasting horizons • Energy prediction in buildings	• Solar energy
[53]	2020	• AI models • RF • Bayesian optimization • Genetic algorithm • Modified harmony search • Wavelet and Fourier series	• Lack of focus on renewable energy sources • Data pre-processing techniques in renewable energy predictions • Need for improved parameter selection methods in models	• Solar energy • Wind power • Hydropower • Biomass • Waves • Geothermal
[54]	2020	• GA • RF • PCA • ENS	• Building functionality and climate change effects • No optimal criteria combination for accurate ML-based forecasting	• Solar energy
[55]	2020	• ARMA • Cuckoo search Algorithms	• Precise accuracy of different models	• Solar energy
[56]	2020	• AI models	• Precise accuracy of different models	• Solar energy
[57]	2021	• AI models • SSAE	• Variation in locations and weather • Multistep ahead forecasting	• Solar energy
[58]	2021	• DBN with GA • DLSTM • Hybrid algorithms	• Precise wind, solar, and power demand forecasting • Big and small heterogeneous data	• Solar energy • Wind energy
[59]	2021	• DL models • DTL • PVPF • Online Learning	• Limited research on the use of deep transfer learning for PV systems • Forecasting periods compared to short-term forecasting	• Solar energy
[60]	2022	• DL • ML • RF • AI	• Finding optimal values and Variations in efficiency, robustness, accuracy values, and generalization capability • Parameter selection for modeling	• Solar energy • Wind energy
[61]	2022	• AI models	• Variations in efficiency, robustness, accuracy values, and generalization	• Solar energy
[62]	2023	• AI models • PCC • SSA	• Precise forecasting of PV system • Inconsistent distribution of solar irradiation and temperature	• Solar energy

provided for 147 days of NREL data. The authors also found that adjustable MLP variables and the parameters of the DL can significantly improve the convergence of the algorithm and reduce errors.

The authors of [64] investigated how deep learning (DL) techniques can be implemented in power grids. The study describes an LSTM-based prediction of solar radiation for 1 hour, 1 day and 1 year ahead. Data for one year ahead is important for system planning and the market. This study provides an overview of the full range of DL methods currently used for electricity systems.

Independently produced ground-based and satellite-based predictions of solar irradiance are compared in [65]. The productive exchange of predictions and results is analyzed. The paper suggests that satellite-based datasets can be used as input for solar predictions. The results of calibration refinement and the definition of related terms are also described in the study. 1-hour forecasts for the GHI for one year using three years of xg and xs data are discussed in the study.

The study at [66] examined both empirical and ML methods for predicting global solar irradiance from air temperature input. Daily global solar radiation prediction in temperate continental regions is performed using 4 ML and 4 empirical temperature-based approaches. Simulation results showed that the hybrid GA and ANN strategy outperforms state-of-the-art ML and empirical models. Therefore, the temperature-based hybrid model is highly recommended for GHI prediction in temperate latitudes and is crucial for the management and operation of solar energy systems.

The application of ML techniques to the prediction of solar radiation for planning purposes is the focus of [67]. Predictions based on historical data using linear regression (LR), regression tree and support vector machine models are proposed. The models use past weather data to make predictions about solar radiation. Parameters such as wind speed, air pressure and humidity are included in the model input. The proposed approach could help grid operators to better manage supply and demand.

The long-term prediction of solar irradiance for the design and layout of microgrids is discussed in [68]. The research examines various DL methods for predicting hourly and daily solar irradiance for the coming year. Both past solar irradiance data and GHI over the open sky were recommended for the models. Models such as Feed-forward neural networks (FFNNs), support vector regression (SVR) and gated recurrent units (GRUs) were evaluated. The paper concludes that GRU performs relatively better compared to the other models. In addition, the study also explains how the various ML models work.

In [69], a novel method using a DNN is proposed to recognize and evaluate the effects of transient meteorological conditions on videos. Particularly, the time-lapse video recordings from upward-facing wide-angle cameras are used to directly estimate and predict solar irradiance. The proposed DL method reduces the current MAE in estimation and prediction. The proposed prediction architecture uses level 1 modeling, where individual images are encoded with short lookbacks to produce a representation of the entire sky, and then uses an RNN-LSTM neural network to convert historical photos into a 128-vector graphical representation. All models have difficulty predicting irradiance in the early morning and late evening.

Four different ML algorithms are used to predict the daily global radiation for the four provinces of Turkey in [70] using SVM, ANN, kNN and DL are used. Seven statistical criteria are used to determine the efficiency of these algorithms in this study. The results show a high accuracy, with the ANN algorithm performing best among all algorithms.

The study at [71] investigated the application of ANN for solar radiation and photovoltaic (PV) prediction in Nigeria. The aim of the study is to develop ANN methods that can provide hourly predictions of solar radiation. Predictions of solar radiation and PV variables are possible with the known methods. The R2 values for ANN techniques are between 0.9046 and 0.9777 for the prediction of solar irradiance and between 0.7768 and 0.8739 for a variety of PV parameters. The study concludes that the development and implementation of photovoltaic systems for power generation in Nigeria is recommended.

The accuracy of solar irradiance prediction using 6 different ML methods for Turkey and the United States is discussed in [72]). Gradient boosting tree (GBT), multilayer perceptron neural network (MLPNN), 2 classes of adaptive neuro-fuzzy inference systems (ANFIS) based on fuzzy-c-means clustering (FCM) and subtractive clustering based ANFIS (ANFIS-SC), multivariate adaptive regression splines (MARS), and classification & regression-tree-CART were used in the study. RMSE, R, MAE and NS were used in the study to compare model accuracy. The GBT model predicted solar energy and radiation better than the other models.

Electricity generation from renewable energy sources, in particular from photovoltaics (PV), is discussed in [73]. The proposed model uses a DL block cell and genetic algorithm (GA) optimization to predict solar irradiance time series. The effectiveness of three different neural network models, namely long short-term memory (LSTM), gated recurrent unit (GRU) and radial basis function (RBF), is compared in the study. The optimization of the window size and the number of neurons in each of the three hidden layers is possible using a genetic algorithm. The algorithm was developed in Python and uses KERAS, a deep learning package that supports both CPU and GPU.

In [74] a method for predicting solar irradiance for several time horizons is proposed that considers 3, 6 and 24 hour conditions. The proposed model uses an LSTM network that considers the hours between the common day and others. The algorithm has an optimized number of neurons and is measured using industry accepted metrics, namely standard deviation and root mean squared error. Low values of mean squared error and mean absolute error in percentage indicate the effectiveness of the proposed model.

A novel method to use machine learning techniques for estimation of short-term GHI from images of the sky is presented in [75]. Proposed algorithm provided features from sky images for solar irradiance prediction. The efficiency of the proposed machine learning algorithm is evaluated on 2 publicly available sets of sky images. Compared to the state-of-the-art algorithms in the literature, the proposed approach performs well and has much lower computational cost for both nowcasting and forecasting up to 4 hours ahead. The study also discussed the challenges in renewable energy forecasting as the natural energy sources exhibit unpredictable behavior.

Effectiveness of unsupervised and supervised solar power forecasting using machine learning algorithms that utilise tree-based approaches integrating implicit and explicit regime detection techniques is evaluated in [76]. The study evaluated the ML methods for solar power forecasting in Kuwait. The regime dependent models ANN are subjected to a comprehensive investigation to reduce the prediction errors on a test dataset and computed on an independent validation dataset. The explicit regime-dependent method performs worse than the tree-based regression model approach. The study found that tree-based methods, especially the regression model tree method, are more suitable for solar power forecasting.

Two ML algorithms, the multi-layer perceptron artificial neural network (MLP-ANN) and genetic programming (MGGP), are used for the prediction of solar irradiance in [77]. The irradiance predictions at 6 locations are analyzed with MLP, MGGP and persistence over horizons from 15 to 120 minutes. The overall improvement of the mean squared error (MSE) is 5.68% and the improvement of the RMSE is 3.41%. Iterative predictions improve MGGP accuracy. MGGP provided more accurate and meaningful estimates and faster solutions in certain situations, while ANN is more complex and requires more computational effort. In this study, the authors used a feed-forward design of NN-MLP with 10 neurons and hidden layers with a hyperbolic tangential sigmoid transfer function.

Deep learning approaches for predicting solar irradiance and PV system performance are investigated using time series data in [51]. The simulations are evaluated based on input data, forecast horizon, season, training time and results accuracy. LSTM shows the best result among the individual models, while the hybrid model CNN-LSTM is superior to all models but requires more training time. RMSE is recommended as a representative evaluation measure for the accuracy comparison among applied models.

The authors of [52] propose a hybrid DL model that integrates a GRU-NN and an attention process for the accurate prediction of solar irradiance variations. DL model was created to extract features from the available dataset using Inception and ResNet-NN. Subsequently, the extracted features are fed into a recurrent neural network (RNN) to train the DL model. The experimental results show that the proposed hybrid DL model outperforms the traditional DL models on the basis of MAE, RMSE and MAPE. Prediction of hourly solar energy in South Africa using ML approaches is discussed in [53]. The study compares the prediction results of short-term solar radiation prediction with recurrent neural networks, LSTMs, FNNs and Quantile regression averaging (QRA). The FFNN approaches provide the most accurate prediction in terms of the MAE and MSE.

A family of flexible and robust DL methods for solar irradiance prediction are presented in [54]. Solar irradiation locations are ideal for these methods as new sensors can be added or deleted as needed without the need to update the model. The models are trained based on the prediction of solar radiation at several locations simultaneously. The models are designed to be as independent as possible from the number and location of data sources used for their training. The study also emphasised the need for solar prediction models for the smart city to be flexible and robust.

In [55] authors have proposed methods for prediction of daily solar radiation at two locations in India using DL techniques and data from numerous locations. The aim of this study is to discover and implement ML techniques for detecting latent symmetry in data patterns and relationships. Comparison of rolling window metrics such as MSE, RMSE and R2 shows the performance of the proposed model. There is evidence that bidirectional and attention-based LSTM techniques can predict daily GHI data. The research shows that sustainable planning of solar energy systems and estimation of available solar energy at specific locations can benefit from the application of hybrid approaches that combine linear and nonlinear methods.

A model for the short-term prediction of solar radiation is proposed in [56] using spatio-temporal weather dependencies between regional systems with the help of ResNet and LSTM. To assess how well the proposal works, it is compared with a number of different DL methods. The ResNet/LSTM ensemble model makes better predictions than the others. The typical evaluation is based on MAE and RMSE. Specific and temporal correlations improve the prediction of solar irradiance with the proposed approach.

A novel solar irradiance prediction model is proposed in In the study at [57] that uses ML and spatio-temporal factors to make accurate 10-minute predictions of solar irradiance. The proposed forecasting model can be combined with PV systems to forecast their output power and promote their integration into the smart grid. The study also discussed the accuracy achieved with other models and compared it with the proposed model. The study shows that the RMSE decreases in both the training and validation phases when the configuration delay is 1:2 and the hidden layer has 10 neurons.

An intra-day solar irradiance prediction using satellite-based estimates for PV power plants is proposed in [24]. The proposed method relies on a sophisticated neural network fed with a collection of time-dependent irradiance estimates from satellite images taken in the vicinity of the target area. Performance is improved even without irradiance observations, as shown by a comparison with the accuracy of the european centre for medium-range weather forecasts (ECMWF) and studies using similar methods and forecast horizons. The report proposes various further work to improve the model. All GHI irradiance data are available for examination, which improves reproducibility.

In [58], authors have described a machine learning model for prediction of solar irradiance using a sky camera. This method used LSTM DL algorithm to make predictions about where the clouds will be in the next ten minutes. The information about cloud cover is obtained by processing images of the sky. The proposed method outperformed the persistence model in scenarios with large variations in solar irradiance, including partly cloudy days. The predictions were categorized into three groups depending on whether the sky was clear, partly cloudy or overcast. The method for predicting solar radiation consists of two steps: Calculation of cloud cover using sky image processing, projection of future cloud cover using the LSTM, and prediction of GHI using input data from the cloud cover solar radiation model. The LSTM model consists of a GRU gate: forgetting, input, output and a cell state.

Short-term predictions of solar radiation is focused in [59] with the aim of accuracy improvement. The proposed approach includes MC, RPCA, spectral clustering and NN. Spectral clustering is used to minimize the influence of weather periods on solar irradiance. Experimental results show that the proposed method improves the accuracy of solar irradiance. The study describes in detail the ML techniques used in the strategy that contribute to the regulation of solar energy fluxes.

The study [60] proposed a ML approach for cloud segmentation to estimate solar power output. The study compares several methods, including different machine learning models. U-Net, a deep neural network, was used to correctly partition the cloud pixels. Sunlight has a direct influence on cloud cover. Therefore, solar output can be estimated using machine learning techniques and sky-facing cameras. The study also addresses the difficulties in recognising cloud edges and thus separating clouds from clear skies. Therefore, all types of clouds are segmented as the same class: clouds.

A multi-task ML algorithm is proposed in [61] for solar irradiance prediction. The LSTM neural network model is used to implement the proposed strategy, and its performance is evaluated by predictions on many time scales such as 1 hour, 1 day and 1 week. A hybrid chicken swarm optimizer, which combines the best aspects of the chicken swarm optimization algorithm (CSO) and the grey wolf optimization algorithm (GWO), is used to predict the hyper parameters of the proposed LSTM approach. An effective tool for allocating resources between tasks is presented in this paper.

Various machine learning algorithms for the prediction of solar radiation and its impact on extreme weather events is discussed in [62]. The authors applied twelve machine learning models to accurately predict and compare daily and monthly solar radiation measurements. The meteorological conditions significantly influenced the machine learning models. GBRT, XGBoost, GPR and Random Forest models predicted daily and monthly solar radiation better. If only a few data points are available, the study recommends using the XGBoost model to predict solar radiation. It also discusses the importance of variable selection when creating machine learning models.

The survey at [78] presented papers published between 2009 and 2019 and discussed the use of meta-heuristic algorithms to solve feature selection problems. The purpose of feature selection is to reduce the size of the feature set without compromising performance. In this study, meta-heuristic algorithms are divided into four different categories according to their behavior by considering binary variants of meta-heuristic algorithms. In addition, a study of UCI repository datasets for optimal feature subset extraction is presented in this survey. Some research gaps, challenges and problems in extracting the best subset of features using different meta-heuristic algorithms are highlighted. Study also investigated the fact values of meta-heuristic algorithms that may lead to premature convergence. In the research, the bio-informatics-oriented Matthews correlation coefficient (MCC) is introduced as a binary quality measure for classification.

An ensemble model of wavelet transform (WT) and BiLSTM-deep learning network for 24-hour global horizontal solar irradiance prediction is presented in [79]. The wavelet decomposition components D1 to D6 are combined in this work to reduce the number of intrinsic model functions (IMF). Separate BiLSTM networks learned in isolation are used for each IMF. Full solar prediction GHI is reconstructed using the predictions of the BiLSTM networks for different values in sub-series. Compared to existing models, the proposed model has better RMSE, MAPE, R2 and FS results. This model reduces the monthly average RMSE by 26.041-58.890%, 5.170-31.350%, 23.260-56.060% and 21.080-570% compared to standalone BiLSTM and GRU& LSTM networks. However, benchmark, standalone BiLSTM, GRU and LSTM had lower monthly average MAPEs of 9.518%, 12.59-28.14%, 30.43-59.19% and 26.54-58.92%, respectively.

A Deep learning based model is proposed in [80] for the prediction of global horizontal irradiance for 1 hour. The method categorizes GHI time series data into multiple clusters using deep learning-based time series clustering to reveal unique patterns and improve clustering efficiency. The DNN-FADF is created independently for each cluster for use in GHI prediction. The simulation results show that the proposed approach provides the most accurate solar forecasts compared to smart persistence and state-of-the-art models. The RMSE decreases by 11.88% with the proposed strategy and by 12.65% compared to Smart Persistence. In contrast to previous studies, the FADF training uses the Huber loss and not the MSE.

The accurate prediction of solar irradiance is crucial for the optimal management of solar energy systems. The limitations of current statistical and machine learning methods in providing accurate predictions are highlighted in [81]. DL models have been proposed as a solution to mitigate these drawbacks and improve prediction accuracy. The utility and efficiency of various DL models, including LSTM, DBN, ESN, CNN, etc., have been investigated. In addition, the use of hybrid approaches to further improve the prediction performance is discussed in the study.

In [82], a forecasting model is proposed that can predict solar irradiance in very short time periods, especially for 10 minutes in advance. Two ANN-based techniques are developed in the study: LSTM and CNN. According to the results, the CNN is more accurate. In the test phase, an RMSE of 52.580 W/m2 was measured. The proposed model provides reliable predictions that can be used in a PV generation strategy to improve grid integration.

In view of the variable solar radiation and changeable weather conditions, solar and wind energy prediction is focused in [83]. During ANN training process, the

HSA-optimized weights are applied to the edges of the ANN with the original sequence. Using a HSA-optimized ANN, the authors of this study provided a reliable and accurate model for prediction of solar and wind energy. The simulation results show that the proposed HSA-optimized ANN models are more accurate than existing solar and wind energy prediction methods. For solar irradiance prediction, the HSA-optimized ANN model achieved MSE = 0.047540, MAE = 0.185460, MAPE = 0.324301% and RMSE = 0.218050; for wind speed prediction, the HSA-optimized ANN model achieved MSE = 0.309440, MAE = 0.471720, MAPE = 0.128960.

An ensemble model based on machine learning is proposed by the authors of [84] to predict solar irradiance. The paper compares mean and weighted mean ensemble models using RF, XGTs, CB and AdaptiveBoost. Clustering algorithms are used to organize weather data, with inputs such as feature selection and previously observed values. The RF-CB method of weighted mean tuning outperforms the individual ML algorithms and ensemble models.

We present a summary of the existing literature on solar irradiance forecasting in table 4 emphasizing it as an active and evolving field of study. Table presents the different techniques and methods used in the various studies and highlights the continuous efforts to improve prediction accuracy. Table also outlines the objectives and contributions of each study and highlights the different approaches and innovations in this area. Evaluation metrics such as nMAP and RMSE are used to assess the performance of the models, reflecting the importance of accuracy in prediction. The potential future work include generalizing the models to other regions and improving interval estimates, indicating the potential growth areas in solar irradiance prediction research.

IV. MATERIALS AND METHODS

In accordance with preferred reporting items for systematic reviews and meta-analyses (PRISMA) 2020 [85], a comprehensive literature search was conducted to find the most relevant and up-to-date research on solar radiation prediction. First, the databases ScienceDirect, IEEE Xplore, Web of Science, Springer and MDPI were searched for articles published between 2015 and 2023. among many, a total of 37 articles were finally shortlisted that met all the requirements for conducting the study. The focus of these reviews and technical articles was on the problems and difficulties associated with solar irradiance prediction and its various applications.

A. SEARCH KEY PHRASES

Following search key phrases were used during searching of relevant literature.

Solar energy, Irradiance, Forecasting, Applications and Challenges

B. DATABASES

Search string was executed on following databases.

Science Direct and IEEE Xplore, Web of Science, Springer and MDPI.

C. INCLUSION AND EXCLUSION CRITERIA

During literature search following inclusion and exclusion criteria were used, as shown in Table 5.

V. SWOT ANALYSIS

A strengths, weaknesses, opportunities and threats (SWOT) analysis provides a comprehensive understanding of the current state of knowledge of the domain by identifying its strengths and weaknesses. In this section we present a SWOT analysis about the AI-based solar irradiance prediction models which provides a detailed examination of the advantages and disadvantages, potential growth areas and challenges facing the solar energy sector. It serves as a guide for stakeholders to understand the factors influencing the adoption and development of solar energy. SWOT analysis is summarized in Figure 10 whereas, precise description of the analysis is presented in the following.

A. STRENGTHS

Solar energy is regarded as renewable, environmentally friendly and practically inexhaustible. The major strength of solar engy is its lower operating costs, thus it can significantly reduce electricity bills. It also generates clean electricity without the emissions of green house gases that leads to an eco-friendly environments.

B. WEAKNESSES

The SWOT analysis identifies several weakness such that the solar energy generation is dependent on solar radiation, and the availability of solar irradiance may be irregular due to weather conditions and the time of night. Furthermore, the initial setup cost of installing solar panels is also on the higher side. The initial cast increases for the large installations that require a lot of land.

C. OPPORTUNITIES

Research and development work is constantly being carried out to improve efficiency and reduce costs. There are also government incentives to promote the use of solar energy, which can reduce a country's dependence on fossil fuels and increase energy security.

D. THREATS

The fossil fuel industry may view solar energy as competition, and policies affecting the industry may change suddenly due to government support or regulatory impact. The global supply chain is susceptible to disruptions that may impact production, and there may be resistance to installations due to aesthetic or land planning concerns.

VI. RESEARCH CHALLENGES

In the field of solar irradiance prediction research, several technological and practical challenges need to be overcome

TABLE 4. Summary of literature on solar irradiance forecasting.

Paper	Year	Architecture / model	Objectives / contributions	Accuracy	Future work
[30]	2015	• HMM • SVM	• ML-based short term forecasting for advanced forecasting	• 64.6% • 73.1%	• Focus on data fusion technology
[63]	2018	• MLP • RF	• MLP and RF based forecasting using a 6 months UTSA SkyImager dataset	• MAE = 81.21 • MAPE = 33.05% • MAE = 66.86 • MAPE = 28.00%	• Detailed analysis of optical flow
[64]	2019	• LSTM	• DL technique (LSTM) in power systems	• MSE = 10.4	• Not mentioned
[66]	2019	• MEA-ANN • RF	• Compared ML and empirical models	• RMSE = 2.814 • MBE = 0.255 • RMSE = 3.103 • MBE = 0.334	• ML models for predicting GHI with satellite data
[67]	2019	• Regression tree • SVM-RBF	• Solar irradiance prediction	• r^2 = 0.6 • r^2 = 0.94	• Model with more weather inputs like Dew Point, Sky Cover
[65]	2019	• SVR • Ensemble	• Earth and satellite-based solar forecasts	• nRMSE=27.46% • nMBE=2.04% • nRMSE=27.53% • nMBE=1.31%	• Not mentioned
[69]	2019	• GFS • DNN	• DL-based short term solar prediction	• nMAP = 110.5 • nMAP = 31.6	• Aggregate video-feed from several sky-cameras
[71]	2020	• ANN	• ANN-based solar irradiance and solar PV forecasting	• RMSE = 89.63 • MAE = 39.62 • R = 0.96	• Development of an ensemble model
[73]	2020	• LSTM-GA • GRU-GA	• Short-term solar irradiation forecasting	• MSE 0.0015 • MAE = 0.027 • MSE = 0.0017 • MAE = 0.029	• Use of application for simulation design, installation and planning of renewable energy in micro-grids
[74]	2020	• LSTM	• Multi-step hourly ahead 3/6/24 hours of the same day forecasting	• RMSE = 0.099 • MAPE = 4.54%	• Hybrid ARIMA-LSTM model
[75]	2020	• KNN-based approach	• Short term solar irradiance estimate from sky images using ML method	• nMAPE = 14.90% • RMSE = 122.20 • RMSE = 7.7%	• Implement the proposed algorithm on a low-cost sky imaging system
[77]	2020	• MGGP	• Evaluate the performance of MGGP	• MAE= 5.68% • RMSE= 3.41%	• Training speed improvement
[79]	2021	• LSTM • BiLSTM • Ensemble method	• To propose an ensemble model using the WT and BiLSTM • DNN to forecasting 24-hour ahead solar irradiance	• RMSE = 40.33 • RMSE = 33.57 • RMSE = 31.83	• Use wavelet families on forecasting accuracy
[80]	2021	• GRU • Hybrid	• 1-hour ahead GHI DL-based forecasting using clustering method	• RMSE 117.35 • RMSE 112.10	• Using CNNs and RNNs for incorporating more features
[82]	2022	• LSTM • CNN	• Very short-term solar irradiation forecast up to 10 min ahead	• RMSE= 5.65 • RMSE= 5.07	• Improvements in accuracy
[83]	2022	• HSA optimized ANN	• Reduces the CO_2 emission and operation cost	• MSE = 0.0475 • MAE = 0.1854 • MAPE = 0.324% • RMSE = 0.21805	• The accuracy test for wind speed forecasting
[84]	2023	• Ensemble voting method	• compare simple and weighted average to evaluate the performance with other algorithms	• MAE =6% • RMSE =3% • MAPE =1%	• Weights selection in average voting

TABLE 5. Inclusion and exclusion criteria of the current study.

Inclusion criteria		Exclusion criteria
Time line	2015 to 2023	Articles beyond the year range
Types of articles	Research, Review, Book chapters, Edited books	Articles in the pre-publication stage
Article venue	International conferences, Peer reviewed journals, Book chapters, Edited books, Magazine	Editorials, notes, and other short type of publications.
Access type	Open access and subscription-based	Articles where the abstracts did not focus on the targeted subject.
Keywords	Solar energy, Irradiance, Forecasting, Applications and Challenges	Articles where the title did not match the desired keywords/subject.

FIGURE 10. SWOT analysis of solar energy.

to improve the accuracy and reliability of solar energy prediction systems. The main challenges in this area are listed below:

A. DATA QUALITY AND AVAILABILITY

Predictions for solar irradiance is highly dependent on the quality and availability of data in solar irradiance forecasting systems, which is a major research challenge. Accurate solar irradiance predictions are essential for maximizing the efficiency of solar energy systems; however, incomplete or inconsistent data can compromise these predictions. To improve the quality of data, researchers must concentrate on using sophisticated data assimilation techniques, integrating a variety of data sources and implementing rigorous validation procedures. Creating plans to capture data in real time and filling gaps in historical datasets are two ways to improve data availability. Overcoming this obstacle will help to predict solar irradiance more accurately, which will facilitate and promote the development of sustainable solar energy sources.

B. PHYSICAL PARAMETERS AND METEOROLOGICAL FACTORS

Weather, meteorological and physical parameters can significantly influence the general predictive accuracy of the solar system. Meteorological influences can result from changes in the weather. Meteorological factors such as temperature, wind speed, air pressure, maximum and minimum temperatures, relative humidity, sunshine duration, land surface temperature, cloud cover, forecast horizon and weather classification can all affect forecast accuracy. Monitoring the performance, yield and efficiency of solar installations is critical for risk assessment and grid management of physical parameters.

C. CLOUD COVER AND ATMOSPHERIC EFFECTS ON SOLAR IRRADIANCE PREDICTION

Understanding how cloud cover and atmospheric factors affect solar irradiance forecasting systems is a key challenge for research in order to optimise the use of solar energy. Unpredictable variations in solar radiation caused by clouds affect the accuracy of energy predictions. The development of more accurate and reliable solar prediction models that distinguish between different cloud types, take atmospheric aerosols into account and can adapt quickly to temporal changes is an urgent imperative.

D. RESOURCE ASSESSMENT FOR EMERGING SOLAR TECHNOLOGIES

To improve the reliability of renewable energy, the critical research task of resource assessment for the development of solar irradiance prediction technologies must be addressed. This requires evaluating the performance of innovative prediction models under different geographical and climatic conditions. Scientists are focusing on the optimization of algorithms, the integration of real-time data and the management of solar irradiance variability. An accurate assessment of available resources guarantees informed decisions when introducing new solar technologies, ensuring maximum energy yield and facilitating the transition to creative and sustainable solar solutions. By improving the accuracy of solar energy predictions, this research helps to maximize the use of sunlight and increase electricity generation. Ultimately, improvements in resource assessment are critical to promoting the effectiveness and sustainability of solar forecasting technology development.

E. REGULATORY AND POLICY CHALLENGES

The difficulties in predicting solar irradiance resulting from regulations and policies have a significant impact on how renewable energy is integrated into the current framework. Researchers face the challenge of coordinating forecasting models with various regulatory and policy frameworks, ensuring compliance and creating a conducive atmosphere for solar technologies. Challenges include standardizing forecasting techniques, dealing with privacy issues, and dealing with complicated energy regulations. Successfully overcoming these obstacles will require interdisciplinary collaboration between meteorologists, legislators and technologists.

F. DATA COLLECTION AND PROCESSING

Reliable and accurate predictions require data processing, data history management and data collection. Since solar irradiance data are available from various sources, effective data acquisition techniques should be used to process the available data. Factors that play an important role in solar irradiance forecasting include: diversity of data sets, time steps, forecast horizons, frames, performance metrics, biases in satellite-based data, correction biases, insufficient sensor calibration, inadequate equipment, and detection of irregular patterns in the data.

G. ACCURACY, STABILITY AND PREDICTION

The correct initialization of the model and the inclusion of real-time observational data in the prediction models are two of the biggest challenges in improving prediction accuracy. This challenge has to do with the application of machine learning algorithms to predict solar irradiance, especially with training and test datasets for a given scenario. Since the efficiency of the algorithm depends on how the applications are implemented, it has properties such as accuracy, stability of results and predictive power. The accuracy of these algorithms depends on the caliber of the training data. An accurate forecast is essential for the stability of the energy system. It is possible to categorize the input data used in the prediction models as endogenous or exogenous to deal with additional data sources resulting from an increase in the number of devices, and then compare different solar prediction algorithms for accuracy. Cameras pointed at the sky cannot always measure the cloud cover index (CCI) due to the segmentation of cloud pixels. Another important area that the research community should focus on is the prediction of solar irradiance over multiple time scales.

H. TOPOGRAPHY AND TIME INTERVALS

The direction of incidence and the ambient temperature determine the amount of solar radiation. Solar irradiance can vary considerably over short time intervals and distances. It can be a challenge to create models that account for these variations in order to make accurate predictions, especially in locations with complex topography. Solar irradiance prediction algorithms need to be developed that can account for the spatio-temporal effects on power generation to fully utilize the inherent temporal and spatial characteristics.

I. HYBRIDIZATION OF MACHINE LEARNING ALGORITHMS

To leverage the unique advantages of each algorithm and mitigate the disadvantages of each model, machine learning algorithms are hybridized. Compared to using a single algorithm, this method aims to build a more reliable and effective system that can perform better. Prediction models and machine learning algorithms that take into account the dynamic and non-linear aspects of solar irradiance prediction need further investigation to develop more accurate and reliable hybrid forecasting models.

J. FORECASTING QUALITY WITH DIFFERENT HORIZONS

Finding a balance between the requirements for short-term (hourly to daily) forecasts for grid integration and long-term (weekly to monthly) forecasts for energy planning can be challenging, as both often require different approaches. Therefore, predicting solar irradiance is a critical requirement for accurate estimation when developing novel systems that can operate in challenging environments.

K. NATURE INTERMITTENCY

Due to the wide range of weather conditions that occur in nature during the different seasons, the solar irradiance in this research task leads to a prediction of the intermittency of solar energy in nature. A common problem with the erratic nature of solar radiation is that it responds differently in different locations, making it difficult to predict how much energy it will generate for PV systems and other systems. Since natural energy sources are unpredictable, it is difficult to predict their use. This limitation could create a space in which new approaches can be developed to solve these problems. Accurately measuring and communicating the uncertainties associated with predicting solar irradiance is essential for energy decision-making, even if it is still a difficult task.

L. HIGHER INITIAL INSTALLATION COST

The initial installation costs for a solar system and a forecasting unit with several sensors are considerably higher. Once the installation costs have been calculated, we need to calculate the design and planning costs of the system, taking into account the initial inaccurate estimate of power generation. Since the design and planning of the solar irradiation forecasting station will have an impact on the prediction of the solar system, the initial installation costs will be higher.

M. BALANCE BETWEEN ENERGY DEMAND AND SUPPLY

A sustainable and reliable renewable energy ecosystem depends on the supply and demand for solar energy being in balance. It is crucial to match the growing demand for solar energy with the capabilities of solar infrastructure and technological developments. To achieve this balance, the use of solar panels must be optimized, energy storage options improved and effective grid management systems put in place. Modern batteries and other storage technologies are essential to bridge the gap between energy production and consumption and ensure a constant power supply even in the absence of direct sunlight. In addition, smart grid technologies enable better distribution and forecasting of demand, contributing to the stability and resilience of the solar energy infrastructure. This balance is key to realizing the full potential of solar energy and transitioning to a sustainable and low-carbon future.

N. INTEGRATION OF SOLAR SYSTEM WITH POWER GRID

In the field of renewable energy, the integration of solar systems into the electricity grid represents a major challenge for research. The seamless integration of solar systems into existing power grids is crucial for optimizing energy distribution and ensuring a constant power supply, especially as global energy demand increases and solar energy becomes more and more important. The challenge for researchers is to develop new technologies and approaches to deal with the fluctuations of sunlight and the erratic nature of solar energy production. To meet this challenge, engineers, physicists and computer scientists must work together across disciplines to develop effective energy storage solutions and sophisticated grid management systems. Furthermore, the successful integration of solar systems depends on research into methods to improve grid stability in times of high solar penetration. This is therefore a challenging but crucial area of research for the realization of a sustainable and effective energy landscape.

O. WEATHER PATTERNS AND SOLAR IRRADIANCE

One of the biggest challenges in the renewable energy sector is to understand and reduce the impact of weather conditions on solar irradiance. Solar power generation is largely dependent on sunlight, and atmospheric factors and cloud cover can have a major impact on how much solar radiation reaches the photovoltaic panels. The task of creating accurate forecasting models that incorporate meteorological data to predict variations in solar irradiance falls to researchers and engineers. Overcoming this obstacle will help solar energy systems become more reliable and efficient, which in turn will improve grid management and resource planning. Maximizing the potential of solar energy and promoting a more resilient and adaptable renewable energy infrastructure requires addressing the complex interactions between weather patterns and solar irradiance.

P. COMPUTATIONAL COMPLEXITY AND IMPLEMENTATION OF PREDICTION ALGORITHMS

At the forefront of solar energy technology development is the research challenge of computational complexity and the implementation of solar prediction algorithms. Accurate prediction of solar irradiance is essential for maximizing the efficiency of solar energy systems. However, sophisticated prediction models can require significant computational effort. Algorithms that strike a balance between computational efficiency and accuracy are an important issue for researchers. To ensure that algorithms can operate in real-time or near real-time, techniques such as machine learning, data assimilation and advanced statistical methods are being explored to improve the accuracy of solar predictions. Solving the problem of computational complexity in solar forecasting is critical to maximizing the use of this renewable resource, improving grid management and successfully integrating solar energy into power grids.

Q. DATA PRE-PROCESSING IN IMPROVEMENT OF PREDICTION ACCURACY

One of the main challenges in solar irradiance prediction research is the improvement of data pre-processing techniques, especially decomposition approaches. This requires developing strategies to effectively manage datasets with many dimensions and different features without losing important information. It is crucial that the scalability of large datasets is taken into account. Moreover, the interpretability of deconstructed representations must be ensured to guarantee the transparency of the model. Overcoming these issues will improve data pre-processing and lead to more efficient and understandable machine learning models in solar irradiance forecasting domain.

R. DESIGNING AND PLANNING OF A SOLAR MICROGRID

The design and planning of a solar microgrid represents a research challenge in the field of efficient and sustainable energy solutions for decentralized solar power generation. Solar microgrids are essential for improving energy resilience and powering isolated or remote areas, as they are decentralized systems that can operate either independently or in conjunction with the main power grid. The design and configuration of solar panels, the integration of energy storage technologies and the application of intelligent control systems are the main research challenges. This challenge involves taking into account variables such as fluctuations in demand, solar energy irregularities and the specific requirements of the industry or community that the microgrid is intended to serve. Addressing this challenge is critical to realizing the full potential of solar microgrids to enable communities to achieve energy independence, reduce their carbon footprint and improve overall energy supply.

S. OPERATION AND MAINTENANCE COST OF SOLAR IRRADIANCE FORECASTING ALGORITHMS

Ensuring the economic viability and efficiency of solar power plants depends on the research task of minimizing the operation and maintenance costs of solar irradiance prediction systems. Although accurate prediction of solar irradiance is critical for maximizing energy production, significant operation and maintenance costs can be incurred. Innovative approaches to increase the reliability of prediction models, reduce the frequency of re-calibrations and speed up maintenance and monitoring procedures are being actively investigated by researchers. These include the use of state-of-the-art machine learning methods, the use of improved sensor technology and the development of automated diagnostic systems. In order to increase the financial viability of solar projects, improve the cost efficiency of solar energy and promote the widespread adoption of clean and sustainable energy sources, this challenge must be successfully addressed.

T. INTEGRATION OF AI AND HYBRID MODELS

The integration of AI and hybrid models to predict solar irradiance offers numerous advantages. Data fusion and feature extraction techniques are helpful to improve the accuracy of machine learning models by capturing complicated, nonlinear relationships in renewable energy systems. The predictive reliability of the models is increased by temporal and spatial patterns. By combining ensemble learning techniques with physically based models, the accuracy of the predictions is further improved. These models are also characterized by their adaptability to dynamic conditions and their resilience through real-time data updates, which guarantees reliable operation. In addition, the use of uncertainty quantification techniques improves risk management and facilitates informed decision making in the context of renewable energy applications.

U. BATTERY BACKUP WITH SOLAR IRRADIANCE FORECASTING SYSTEM

A key challenge for renewable energy research is the integration of solar irradiance predictions with battery backup systems. The inherent volatility of solar energy is mitigated by an effective combination of energy storage and accurate solar forecasting. The research community is working hard to develop complex algorithms that maximize battery charge and discharge cycles depending on predicted solar radiation. This synergistic approach improves the reliability of solar energy systems and ensures a constant power supply even on cloudy days. Solving this problem is critical to maximizing the benefits of solar energy, maintaining grid stability and enabling a smooth transition to a resilient and sustainable energy source in the future.

V. INSTRUMENTATION CALIBRATION ISSUES

Reliable renewable energy predictions depends crucially on the research task of solving problems in the calibration of instruments in a solar prediction system. Optimizing the efficiency of solar power plants requires accurate measurements of solar irradiance. Prediction models can become inaccurate due to calibration problems caused, for example, by instrument degradation or environmental conditions. Focus on the development of advanced sensor technologies, use of traceable reference standards and the implementation of rigorous calibration protocols are the target areas in this regard.

VII. DISCUSSION ON KEY FINDINGS

In this systematic literature review, we addressed three following fundamental research questions (RQs) to gain insights into the landscape of AI-based solar irradiance prediction models.

A. RQ 1: WHAT ARE THE KEY RESEARCH CHALLENGES IDENTIFIED IN EXISTING REVIEW ARTICLES REGARDING AI-BASED SOLAR IRRADIANCE PREDICTION MODELS?

In relation to the research question 1, we identify the main challenges for AI-based solar irradiance prediction models through a comprehensive and systematic review of the existing literature, including both review articles and state-of-the-art research. These challenges range from data quality and availability to model interpretability and the integration of AI techniques with traditional prediction methods. Our study not only lists these challenges, but also discusses them in detail and provides insights into their implications and possible solutions.

TABLE 6. Key findings of the research questions.

RQ	Summary of findings	Addressed in section
RQ1	Identified key challenges include data quality and availability, model interpretability, and integration of AI techniques with traditional forecasting methods.	Section III
RQ2	Common methodologies include machine learning algorithms and numerical weather prediction models. Challenges include model scalability, interpretability, and generalizability.	Section III
RQ3	Emerging trends include the integration of AI techniques with domain knowledge, development of hybrid forecasting models, and exploration of novel data sources.	Section VI

B. RQ 2: WHAT COMMON TOOLS, TECHNIQUES AND MODELS ARE USED IN MODERN RESEARCH TO PREDICT SOLAR ENERGY? WHAT CHALLENGES DOES THE RESEARCH COMMUNITY FACE?

To answer research question 2, we identified common architectures and models used in modern solar energy prediction research by critically analysing their objectives and the accuracy achieved. This analysis and the applicability of these models provide a valuable resource for researchers in the field.

C. RQ 3: WHAT ARE THE EMERGING TRENDS AND FUTURE DIRECTIONS IN AI-BASED SOLAR IRRADIANCE PREDICTION RESEARCH.

In response to the research question 3, we investigated emerging trends and future directions in AI-based solar irradiance prediction. Our study highlights promising areas for future investigation, such as the integration of different AI models to increase prediction accuracy in real-time solar irradiance prediction and the development of models that can account for the effects of climate change on solar irradiance. Key findings of research questions discussed in this study are summarized in Table 6.

VIII. CONCLUSION AND FUTURE IMPLICATIONS

This study has examined the current state of solar irradiance prediction techniques, highlighting both their advantages and disadvantages. The literature review underlines the importance of accurate solar irradiance predictions for the optimization of solar power generation systems. Significant progress has been made in this field, ranging from machine learning methods to numerical weather prediction models. However, there are still difficulties, especially when it comes to how geographical variations and dynamic atmospheric conditions affect forecast accuracy. The complexity of the task is underlined by the multidisciplinary nature of this research, involving data scientists, meteorologists and policy experts. In the future, work on improving the accuracy of current prediction models should be a priority, especially in light of rapidly evolving atmospheric conditions. Current obstacles can be overcome by integrating cutting-edge technologies such as artificial intelligence and real-time data assimilation. There is also an urgent need for international collaboration and standardised methodologies to create a unified framework for solar irradiance prediction. By solving these problems and using cutting-edge technologies, solar energy systems will become more resilient, facilitating their seamless integration into conventional power grids and accelerating the world's transition to sustainable energy sources.

CONFLICT OF INTEREST

The authors declare that they have no known conflict of interest.

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