Chapter 11

Solar Irradiance Prediction and Methods Used in Prediction Studies

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Abstract

Solar energy is considered one of the most important renewable energy sources and is recognized as the fastest-growing energy source worldwide. The power generated in solar energy facilities primarily depends on the amount of radiation reaching the surface of photovoltaic (PV) panels. Prior knowledge of solar radiation is crucial for reliable planning and efficient design of solar energy systems. Therefore, solar radiation forecasting is a highly significant topic. Various techniques can be employed for solar radiation prediction, including fundamental physical and statistical methods, as well as ensemble methods obtained by combining different approaches. However, the remarkable success of artificial neural networks, a form of artificial intelligence application that enhances learning algorithms, in various applications has attracted researchers to this field. The promising potential of this field is evident in the richness of proposed methods and the increasing number of publications. The main objective of this study is to review artificial intelligence-based techniques found in the literature for solar radiation prediction and to identify research gaps by examining radiation predictions using machine learning-based methods and hybrid models created by their combination with other techniques, which have gained popularity recently. Additionally, the aim is to provide an analysis that guides future improvements and understanding of recent advancements in this field. To facilitate and enhance research in this area, a comprehensive review of various artificial intelligence-based prediction methods employed in solar radiation prediction studies, particularly focusing on the most commonly used artificial intelligence-based approach published recently, is presented. Furthermore, information on the required data parameters in solar radiation prediction studies is provided. All research details, fundamental features, and specifics are summarized in tabular and shape formats for a comprehensive overview.

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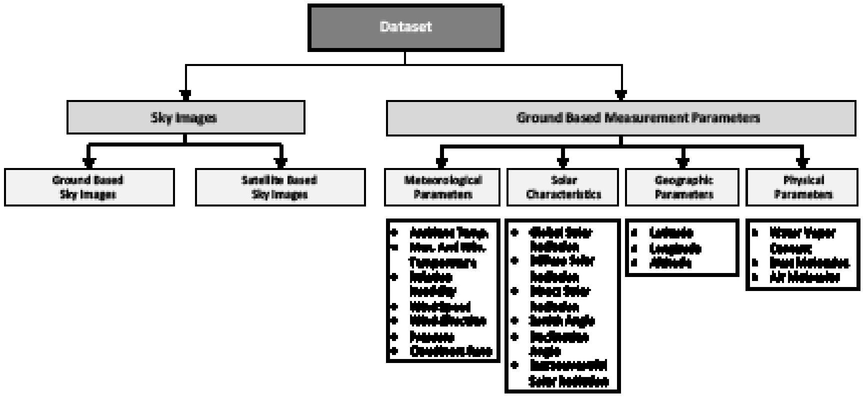
1. Introduction

One of the major challenges for global energy supply in the near future is the large integration of renewable energy sources, particularly unpredictable ones such as wind and solar, into the existing or future energy infrastructure. The variability of renewable energy sources poses even greater challenges. Therefore, it is crucial to effectively predict these sources, especially in order to harness a high proportion of renewable energy.

Solar energy is the most abundant and easily accessible energy source among renewable energy sources. However, due to its dependence on weather conditions, solar energy, being a variable energy source, is not reliable without accurate production forecasting. Each year, the latest techniques and approaches emerge worldwide to improve the accuracy of models and reduce uncertainty in predictions. In particular, solar irradiance prediction is a significant component in solar energy production. Providing forecasts to PV plant managers and grid operators assists in better planning of solar energy storage and utilization of other energy sources. This facilitates the integration and optimization of PV systems with the grid. Additionally, the ability to forecast solar irradiance is valuable for the planning and distribution of electricity generated by different units [1]-[4].

Solar irradiance prediction studies require data from the region for which the forecast is to be made. These data can be obtained through on-site measurements, meteorological stations, or remote sensing via meteorological satellites. The most commonly used data sources are ground measurements, satellite data, and sky imagery. Ground measurement data, typically obtained from meteorological stations, include solar characteristics as well as meteorological and physical parameters. The most widely used measurement devices are pyranometers and pyrheliometers, which measure global horizontal irradiance (GHI) and direct normal irradiance (DNI), respectively. While ground measurements provide accurate and high temporal resolution data, the cost of establishing and maintaining a meteorological network limits its installation in every region. Moreover, the need for continuous operation of measurement devices may lead to calibration issues and maintenance requirements, causing interruptions in data collection [5,6]. Figure 1 illustrates the dataset parameters used in solar irradiance prediction studies.

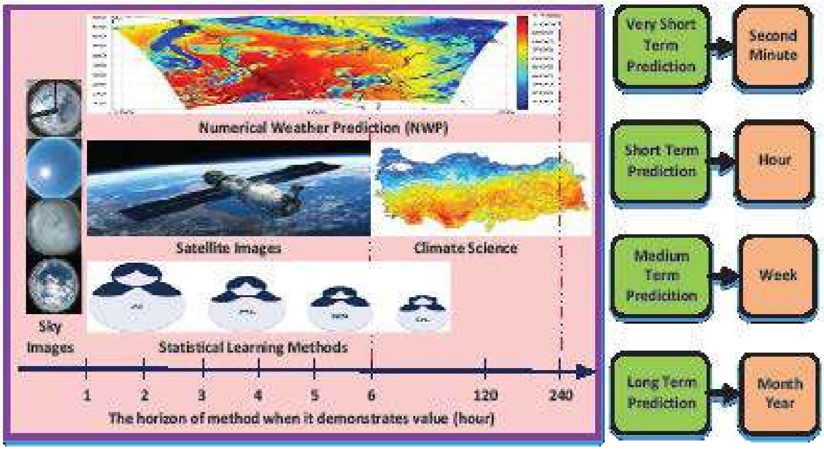
Figure 1. Dataset parameters used in solar irradiance prediction [7]



Prediction studies in the field of renewable energy are crucial for both accurately determining the areas for investment and addressing problems that arise during the operational phase based on preliminary forecasts. Artificial intelligence methods, which exhibit superior characteristics compared to traditional prediction methods and are now being utilized in various fields, are among the most important approaches in prediction studies. Performance analyses indicate that these methods outperform conventional methods. Furthermore, in recent years, researchers have developed ensemble methods to uncover the unique features of individual models and enhance the performance of prediction methods. These combinations provide more accurate results compared to individual models [8].

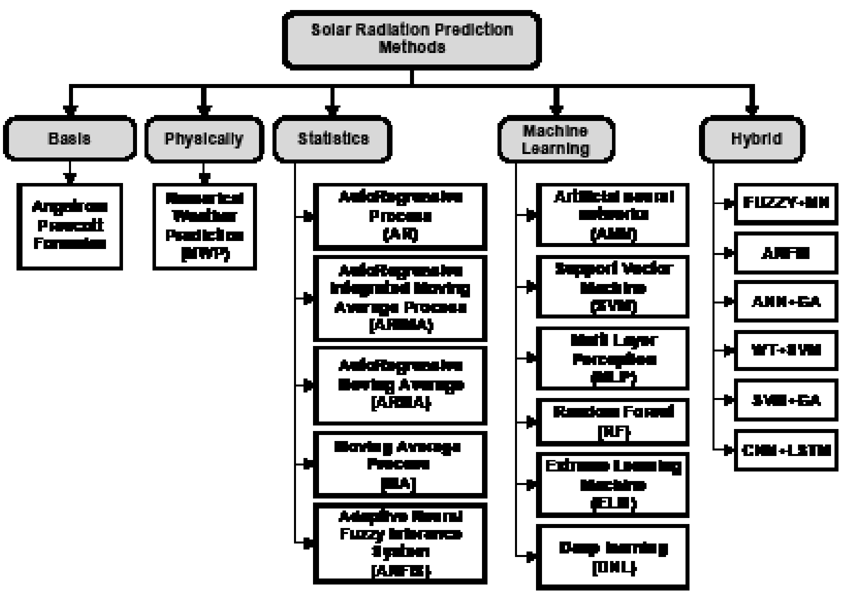
The selection of the prediction method primarily depends on the forecast horizon. However, not all models used have the same accuracy in terms of input parameters and forecast horizon. Predictions are generally classified into long-term (one year to ten years), medium-term (one month to one year), short-term (one day or one week), and very short-term (seconds to minutes). For the development and planning phase of a solar power plant, long-term forecasts are required, while medium-term, short-term, and very short-term predictions are needed for its operation [9]-[11]. Many studies in this field have developed different methodologies for solar irradiance prediction proposed in the last decade. The prediction methods based on forecast horizons and time scales are shown in Figure 2.

Figure 2. Prediction methods based on forecast horizons and time scales [10,11]



Solar irradiance prediction performance and accuracy are important considerations for all researchers. Therefore, it is necessary to interpret the resulting outcomes. Prediction performance is influenced by various factors such as forecast horizon, weather events, and variability in solar energy. The methods used for solar irradiance prediction can be categorized as shown in Figure 3. Essentially, these methods are commonly classified into physical methods, statistical methods, and ensemble methods, which are the most widely used approaches in this field.

Figure 3. Solar irradiance prediction methods [12,13]



2. Solar Irradiance Prediction Methods

2.1. Physical Methods

Physical methods are primarily based on mathematical equations and aim to determine the physical state of solar irradiance and other meteorological conditions [14]. Since the solutions are obtained using numerical methods, they involve numerical weather prediction (NWP), sky imagery, and satellite data. Satellite imagery data is often used for solar irradiance or cloud index predictions and relies on numerical calculations using meteorological data such as atmospheric conditions and ground-based observations to estimate solar irradiance. Cloud movement can be detected using meteorological satellite imagery. As solar irradiance is significantly influenced by cloud structures, determining cloud movement leads to the prediction of cloud positions, which are subsequently used for solar irradiance prediction [15]. Therefore, by applying image processing technologies, solar irradiance at the ground level can be forecasted.

2.1.1. Numerical Weather Prediction (NWP)

NWP systems have long been the foundation of forecasting applications and are powerful tools for predicting solar irradiance. They forecast the likelihood of local cloud formation and indirectly perform predictions by utilizing a dynamic atmospheric model [16]. These models are designed to pre-determine variables such as temperature, humidity, precipitation probability, and wind, and have recently been optimized for predicting surface solar irradiance. NWP models are also used in weather and aviation forecasting. However, they are now preferred models in renewable energy prediction. Satellite information is frequently utilized in NWP models, and predictions can be made up to two days in advance or six days into the future [17,18].

2.1.2. Prediction Model Using Sky Imagers

Sky imagery can provide detailed information about clouds, which is crucial for accurately estimating surface irradiance. Clouds are the most significant factor affecting surface irradiance, making accurate recognition of cloud pixels a prerequisite for surface irradiance calculation. Sky imagers are automatic, full-color imaging systems that use hemispherical lenses to capture and process real-time images of the entire sky from the ground [19]. By processing the images obtained through sky imagers, cloud motion vectors can be derived. These methods can provide solar irradiance predictions with very high spatial resolution (at the meter scale) and temporal resolution (at the minute scale) [20]. For time horizons of less than an hour, techniques based on sky imagery offer excellent prediction capabilities [21]. However, the processes involved in deriving the predictions introduce various uncertainties, leading to relatively low reliability [22]. Accurately calculating solar irradiance using sky imagery can effectively enhance the performance and accuracy of sky image-based FV power prediction models [23].

Recent studies have shown an increase in research efforts towards solar irradiance prediction. In one such study, Ref. [6], a cloud detection method was proposed using multi-level local image patches with different dimensions that incorporate local structures and high-resolution information. The proposed system predicts solar irradiance by utilizing information from all-sky images to complement the limited temporal and spatial resolution of satellite imagery and improve prediction accuracy. Sky images can be obtained using a Total Sky Imager (TSI). In Ref. [24], the authors used this method to track and predict clouds in sky images and estimate irradiance. An optimization model was proposed to determine the cloud motion process. Similarly, in Ref. [25], a solar prediction system was suggested that can detect cloud movements from TSI images and subsequently forecast the future cloud positions on solar panels and the resulting fluctuations in solar irradiance for short-term prediction. Ref. [26] developed a framework for predicting Direct Normal Irradiance (DNI) for a 10-minute time horizon, considering atmospheric variables, including relative humidity, wind speed and direction, DNI, and clouds, directly from historical measurements provided through 24-bit color sky images taken every 30 seconds. In Ref. [27], a new model was created for solar irradiance prediction by matching a total of 7000 images captured with a sky camera at a size of 512*512 pixels with measured Global Horizontal Irradiance (GHI) data from a pyranometer. Ref. [28] introduced a deep Convolutional Neural Network (CNN) model called SolarNet, which was developed to predict operational 1-hour ahead GHI using only sky images without numerical measurements or additional feature engineering. Table 1 provides a detailed overview of application studies using sky imagers for solar irradiance prediction.

Table 1. Methods used for solar irradiance prediction with sky imagers

Method	Prediction Time	Prediction Method
ANN	One hour	BP, CNN, LSTM, CNN+LSTM, SVR
ANN	Ten minutes	AR, MLP, SVR, CNN
Deep Learning	Ten minutes	CNN, LSTM
Deep Learning	Up to four hours	KNN, RF
ANN	Ultra short	BPN
Deep Learning	5-20 minutes	CNN

2.1.3. The Prediction Model Using Satellite Images

Ground-based measurements are limited in terms of geographical coverage, and measurements in these areas may require statistical interpolation, which can lead to large errors for increasing geographical distances [29]. Alternatively, satellite images capture a top-down perspective of the atmosphere and local environment, enabling the monitoring of climate change and solar radiation. Therefore, satellite-based methods have demonstrated the ability to produce more accurate solar radiation predictions compared to traditional interpolation methods [30,31]. Meteorological satellites provide continuous image data of environmental information, such as temperature, wind direction and speed, cloud cover, and radiation, covering a wide range of temporal and spatial scales. Solar radiation models convert satellite images captured by geostationary meteorological satellites into surface radiation by employing methods that combine radiative transfer theory and observations. However, satellite predictions are limited by the spatial resolution of the available databases. Therefore, the spatial resolution of existing fixed meteorological satellites may not be sufficient to conduct a detailed study of solar radiation behavior at a specific geographic location [20,32].

Satellite images have been widely used in recent years to study the atmosphere. Clouds, which significantly attenuate solar radiation, have been investigated by many researchers [33,34]. Since cloud cover is a major factor affecting solar radiation, cloud detection and classification are crucial for predicting solar radiation [35]. Satellite-based solar radiation prediction is useful for short-term intra-day time horizons and outperforms numerical weather predictions with a spatial resolution of 1-5 km and a temporal resolution of up to 4-5 hours [36,37]. The main techniques for satellite prediction are based on advanced cloud motion predictions derived from geospatial satellite images [20]. Satellite images provide information about current and future cloud cover and have the potential to be useful in understanding solar radiation [38]. Sequential satellite images are combined to generate cloud motion vector fields that can be used to predict future cloud positions. It has been shown that this technique is effective in predicting solar radiation intensity from one minute up to six hours ahead.

Satellite images contain all the meteorological parameters at the measurement point simultaneously, depending on the atmospheric conditions. Therefore, the development of solar radiation prediction models using sky imagers and satellite image-based data has become increasingly important. Solar radiation prediction based on satellite data relies on advanced cloud motion predictions derived from geospatial satellite images. Cloud cover-based models can achieve high accuracy in solar radiation prediction since cloud index and sunshine duration are closely related to solar radiation [32]. Table 2 illustrates the satellites and prediction methods used in solar radiation prediction using satellite images.

Table 2. Satellites and prediction methods used in solar radiation prediction with satellite images

<table>
<tr><th>Satellite Name</th><th>Country</th><th>Prediction Models</th></tr>
<tr><td>Spinning Enhanced Visible and Infrared Imager (Seviri)</td><td>EU Countries</td><td rowspan="5">Cloud motion vector (CMV)
Cloud index methodology (CSD-SI)
CLAVR-x
Heliosat
ANN, CNN, SVM, CNN-LSTM</td></tr>
<tr><td>Geostationary Operational Environmental Satellites (GOES)</td><td>USA</td></tr>
<tr><td>Communication, Ocean, and Meteorological Satellite (COMS)</td><td>Korea</td></tr>
<tr><td>Fengyun</td><td>China</td></tr>
<tr><td>Himawari</td><td>Japan</td></tr>
</table>

Cloud Motion Vector (CMV), Cloud Index Methodology (CSD-SI), and CLAVR-x models calculate the speed and direction values determined based on cloud movements observed from satellite images. These values can be used to determine the solar radiation reaching the Earth's surface. Heliosat, on the other hand, is a method that converts observations made by stationary meteorological satellites into global irradiance predictions at the surface level. Hourly and daily irradiance data obtained from satellites are compared with measurements taken at ground-level meteorological stations using pyranometers. The other prediction methods mentioned in Table 2 are explained below under their respective headings.

2.2. Statistical Methods

These methods are artificial intelligence methods, namely machine learning algorithms. They utilize historical data to build a predictive model. Generally, they match input data to output data using statistical techniques to generate predictions. They rely on establishing relationships between past observations and future values [39]. To employ these prediction methods, historical records of solar radiation in the measurement area are utilized, while real-time measurements determine the current conditions on which the predictions are based. They cover a range of applications from short-term to long-term with shorter time steps [40,41]. The prediction methods within this approach yield the best results for intra-hour time horizons but can have values of two to three hours or more when used in conjunction with other methods. They are limited to solving more complex prediction problems when longer forecast horizons are considered [42]. Statistical learning methods are often used to correct errors in NWP model outputs and to blend outputs from multiple models in a process called model output statistics. Current approaches for solar energy prediction focus on a range of supervised and unsupervised learning techniques such as Support Vector Machines (SVM), decision trees, k-nearest neighbors, or Gaussian processes [43]. Methods such as Artificial Neural Networks (ANN) and SVM, which are statistical methods, provide more reliable solutions for predicting global and horizontal solar radiation and power generation [44]. These methods have been previously used for solar radiation prediction and achieved satisfactory performance. Their usage has been validated through studies conducted for different locations and types of solar radiation, solar energy, and wind speed, proving these machine learning methods to be reliable and versatile [45]-[47]. Statistical methods are widely used for prediction in renewable energy systems, encompassing various approaches ranging from classical regression methods to deep learning methods [48]. Table 3 provides commonly used statistical methods for prediction in renewable energy systems.

Table 3. Some statistical methods used for solar radiation prediction

S/N	Statistical Methods	Abbreviation
1	AutoRegressive Process	ARp
2	Moving Average Process	MAp
3	AutoRegressive Moving Average	ARMA
4	AutoRegressive Integrated Moving Average Process	ARIMA
5	Fuzzy Logic	FUZZY
6	Artificial Neural Networks	ANN
7	Support Vector Machine	SVM
8	Deep Learning	DL

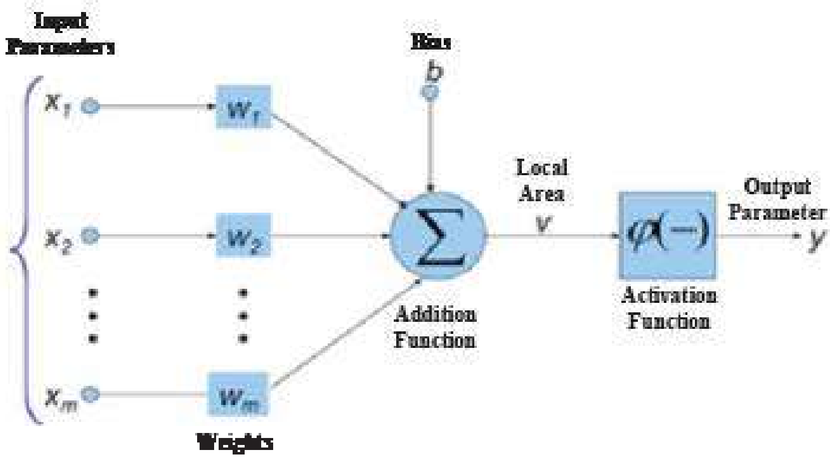
2.2.1. Artificial Neural Networks (ANN)

ANN is an effective and flexible technique widely used in various fields and considered one of the most popular and commonly used networks in the literature [49]. It evaluates the data based on the relationships within the network structure and ensures the inclusion of all factors in the processing. Therefore, the outputs are obtained by considering the weighted evaluation of all factors, rather than using specific formulas. When historical data containing both input and output variables are provided, ANNs can be trained using supervised learning to predict future radiation. The variables used can vary and include on-site radiation measurements, meteorological data, radiation predictions provided by other models, or features obtained from sky or satellite images [50].

ANNs learn patterns from historical data that enable complex mapping between input and output. The training or learning process involves optimizing the model parameters to improve predictions on a training set consisting of input-output pairs [51]. An ANN structure generally consists of input, hidden, and output layers. Additionally, within this structure, there are connection weights, activation functions, and a summation node that combines them. The elements in the input layer, where the inputs are included, can be multiple, and in programs like Matlab, Python, etc., they can only be processed numerically [52]. Relationships are established within the network through the connections using the numerical data taken as input values. Between the two groups of layers, results are generated as many as the number of neurons in each layer. The obtained results can be transferred to the output layer or new layers can be created between the output and computed values to form new connections. This modeling logic can be shaped according to the needs of the study. In the human brain, this process occurs as the destruction of unnecessary connections in cells. In situations where these connections are needed again, they can be reestablished. The brain prevents the storage of unnecessary information in this way, thus saving energy. The smallest unit known as a perceptron in an ANN is expressed by a function as shown in Equation (1) and modeled as shown in Figure 4 [53].

$$y = W * x + b \tag{1}$$

Figure 4. Mathematical model of a neuron.



Here, *x* represents the input values in the input layer, *w* denotes the weights associated with the processing neuron, *b* represents the bias value associated with the neuron, and *y* represents the output in the output layer.

Solar radiation has been analyzed over long periods of time, and it has been predicted using ANNs in different locations [54]. ANNs are more successful than other experimental regression models in predicting solar radiation, and they can be used for both modeling and forecasting solar radiation data [55]. This helps in managing the power generated from a PV system. The performance of ANNs depends on how well they are trained and the quality of the data used. For example, more accurate predictions are generated during clear sky hours compared to cloudy hours. The more accurate the weather forecast parameters used, the more accurate the solar energy predictions can be made.

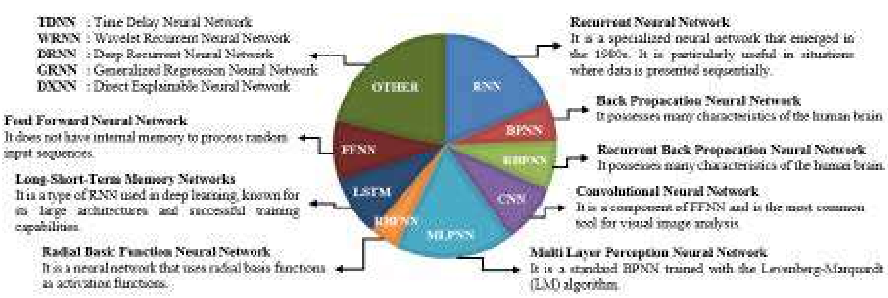
2.2.2. Support Vector Machines (SVM)

Support Vector Machines (SVM) is a kernel-based machine learning technique that was introduced by Vapnik in 1995, although its foundations date back to the 1960s. It is used for classification tasks and regression problems, and it is a supervised learning algorithm that analyzes training data to generate an inferential function [56,57]. SVM is designed not only to minimize errors but also to maximize the margin of separation between different classes. In terms of prediction, SVM yields similar results to Artificial Neural Networks (ANN), but SVM is considered to be easier to use compared to ANN. It is widely used in energy prediction tasks and exhibits excellent generalization capabilities with high prediction accuracy [58].

2.2.3. Deep Learning (DL)

Deep Learning is a machine learning method that utilizes multi-layered deep artificial neural network architectures. Although the initial works date back to the 1940s, the first scientific research incorporating the concept of DL was conducted by Ivakhnenko and Lapa in 1965. While the concept of DL emerged in the 1960s, its prominence has gained momentum in recent times. This is primarily due to the lack of computational power to train deep architectures and the scarcity of sufficient amounts of data during that time. Nowadays, the increase in computational power and the generation of massive amounts of data through digitization have provided the necessary infrastructure for DL. These advancements have facilitated the widespread utilization of DL in various domains such as computer vision, natural language processing, translation, and time series forecasting [59]. Figure 5 depicts the ANN and DL models commonly used in the literature in the field of renewable energy.

Figure 5. ANN and DL models used in the field of renewable energy



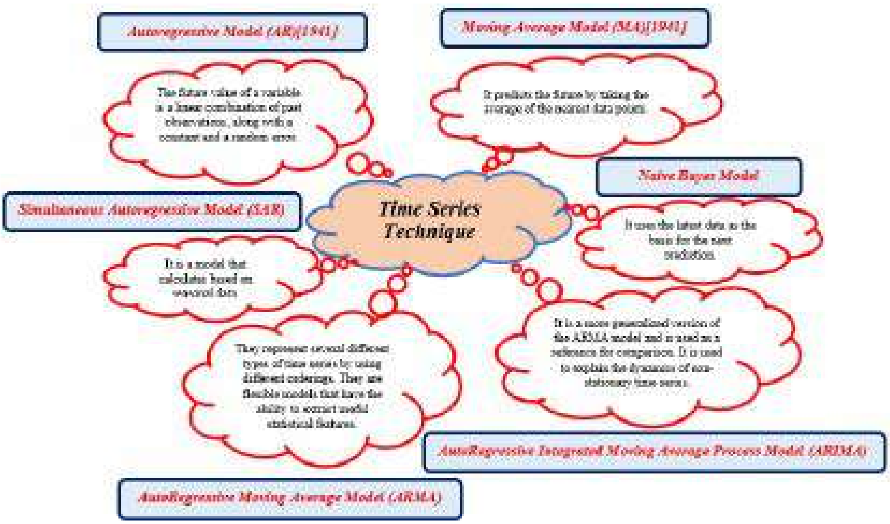
The deep architecture of DL provides support for modeling nonlinear complexities in data, enabling more accurate learning of patterns [60]. As a subfield of machine learning, DL has gained popularity in recent years due to its applicability in various domains [51]. In the field of renewable energy research, DL models, particularly CNN, have been proven to be reliable tools for solar irradiance prediction, wind speed prediction, and PV power output prediction [61,62]. Especially due to its intermittent nature and dependence on various factors such as wind speed, temperature, pressure, and relative humidity, solar data exhibits high-level and nonlinear complex characteristics. These characteristics of solar data are captured by DL models through the extraction of spatial and temporal information. Ongoing research indicates that DL models may outperform ML models in time series, classification, and regression-based prediction problems [63].

When selecting a prediction algorithm, there is a set of criteria that needs to be considered, such as the number of layers, types of layers, activation functions, and so on. These criteria are determined by assessing the performance obtained with certain error metrics when considering different model alternatives. In the field of renewable energy research, DL models, especially CNNs, have been proven to be reliable tools for solar irradiance and PV power output prediction [64]-[66].

2.2.4. Time Series Technique

Time series, which Yule made significant contributions to in 1927, refers to sequentially measured data at specific intervals according to any operation. It represents a chronological sequence of observations related to a specific variable. Time series forecasting can be defined as predicting the future based on past time series data. To determine the prediction model, the fundamental components of a time series, such as trend, cycle, seasonal variations, and irregular fluctuations, need to be identified. Time series data is used to build models using different methods. The process of formulating data appropriately to create a model is called time series analysis. Prediction is carried out through these models, which are primarily based on probability estimates that may not always provide a good generalization for unseen data. Autoregressive Model (AR), Moving Average Model (MA), Seasonal Autoregressive (SAR), Naive Method, Autoregressive Moving Average Model (ARMA), and Autoregressive Integrated Moving Average Model (ARIMA) are approaches based on time series techniques [67,68]. These models show low prediction results when there is weak correlation between meteorological parameters and radiation, and when there are missing or incomplete datasets. Due to the non-stationary behavior of solar radiation data over time, these models cannot accurately capture the non-linearity in the data and therefore exhibit low prediction performance [69,70]. Approaches and features based on time series techniques are illustrated in Figure 6.

Figure 6. Time series techniques and features

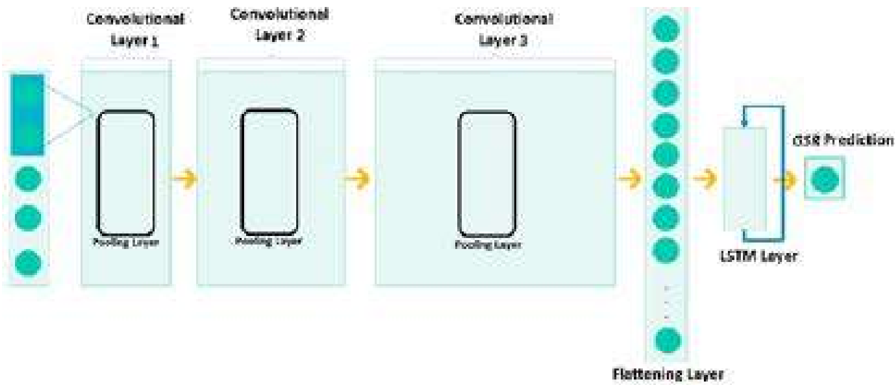


2.3. Community (Hybrid) Methods

Hybrid methods are referred to as techniques that combine different methods to leverage their strong points and overcome the weaknesses of each method. In the literature, several community methods have been proposed by combining physical and mathematical methods with optimization algorithms or machine learning algorithms. This method is essentially a combination of statistical methods or physical methods. In terms of prediction accuracy, it outperforms individual methods. However, it has high computational complexity and therefore takes a long time to reach a result. Additionally, their performance is highly dependent on carefully selected historical inputs [71].

A community consists of a collection of predictions and is an important method to cope with uncertainties, especially in solar energy forecasting. It can identify both linear and nonlinear components in solar time series and overcome any shortcomings of individual models. One of the advantages of the hybrid system is a faster convergence rate [13]. Hybrid models can be modified by adding a deep learning layer, such as Long Short-Term Memory (LSTM), which is a type of recurrent memory, to improve the accuracy of deep learning algorithms. This approach has been shown to enhance the results of solar radiation prediction and photovoltaic power output prediction [72,73]. In general, the CNN+LSTM hybrid model, which combines the CNN structure with the LSTM algorithm, is widely used in solar radiation prediction studies. In this model, the CNN layers are used to extract features of the changes in the input layer related to solar radiation. The LSTM layer, on the other hand, stores the information transferred from the CNN layer in a control unit and provides a new state unit. Figure 7 illustrates the topological structure of the CNN+LSTM hybrid model used in solar radiation prediction studies.

Figure 7. Illustrates the topological structure of the hybrid CNN+LSTM model [74]



Conclusion

Predicting solar radiation is a challenging task as it varies based on the geographical location and meteorological conditions of the specific area under consideration. Therefore, effective modeling of solar radiation prediction methods has garnered significant interest in controlling and operating solar energy generation. This allows for the identification of the most suitable regions for the installation of PV plants, reducing plant costs, maximizing energy production, and ensuring the secure and stable integration of these plants into the grid.

The accuracy of solar radiation prediction models is often influenced by the prediction horizon and climate conditions. While some models perform well under clear sky conditions, their accuracy significantly decreases in fast-changing and variable weather conditions. Additionally, due to the highly complex nature of the solar radiation phenomenon and its crucial importance for solar power plants, simplistic approaches to modeling solar radiation prediction may not yield satisfactory results. Therefore, to improve prediction models and achieve higher accuracy, it is essential to incorporate meteorological data obtained through measurements in specific areas where solar radiation needs to be predicted, capturing the entirety of atmospheric dynamics. By considering these data and accounting for variations in meteorological conditions, more accurate predictions can be made. Furthermore, prediction models constructed using such data will help account for more complex structures and rapid changes in weather conditions, leading to higher accuracy. As a result, the management and planning of solar energy resources, such as solar power plants, can be made more efficient.

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