Journal of Cleaner Production 318 (2021) 128566

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Review

Deep learning models for solar irradiance forecasting: A comprehensive review

Pratima Kumari *, Durga Toshniwal

Department of Computer Science & Engineering, IIT Roorkee, India

A R T I C L E I N F O

Handling Editor: Zhen Leng

Keywords:
Renewable energy
Solar energy
Deep learning
Forecasting
Long short term memory
Deep belief network
Echo state network

A B S T R A C T

The growing human population in this modern society hugely depends on the energy to fulfill their day-to-day needs and activities. Renewable energy sources, especially solar energy, can satisfy the global power demand while reducing global warming caused by conventional sources. Solar irradiance is an essential component in solar power applications. The availability of solar irradiance is influenced by several factors, such as forecasting horizon, weather classification, and performance evaluation metrics, which also need consideration. The accurate forecasting of solar irradiance is of utmost importance for the power system designers and grid operators for efficient management of solar energy systems. The intermittent and non-stationary nature of solar irradiance makes many existing statistical and machine learning approaches less competent in providing accurate predictions. In this context, deep learning models have been proposed by several researchers to reduce the limitations of existing machine learning models and improve prediction accuracy. In this work, an extensive and comprehensive review of deep learning-based solar irradiance forecasting models is presented. The effectiveness and efficacy of several deep learning models, including long short-term memory, deep belief network, echo state network, convolution neural network, etc. have been reviewed. The results obtained in the reported studies proved the superiority of deep learning models in solar forecasting applications. Few researchers have proposed deep hybrid models to improve the prediction performance further. A study reported that the hybrid of CNN-LSTM can enhance the prediction accuracy by 3.62%, 25.29%, 34.66%, 37.37% and 26.20% over CNN, LSTM, GRU, RNN and DNN, respectively. Overall, this paper offers preliminary guidelines for a detailed view of deep learning techniques that researchers and engineers can use to improve the solar photovoltaic plant's modeling and planning.

1. Introduction

Electricity plays a substantial role in the economic and technological growth of a country (Guo et al., 2018). The ever-growing dependence on energy leads to a significant increment in electricity generation globally. The primary sources of electricity production are conventional fossil fuels across the globe. Fossil fuels are on the verge of extinction as they take many years to compose and the existing reserves are being consumed much faster than the new fossil fuels being formed. In addition, fossil fuels are one of the primary sources of greenhouse gas emissions, leading to severe global warming, and therefore threatening the environment and living conditions on which people depend Kumari and Toshniwal (2020b,a). Thus, in recent years, the focus is shifted from fossil fuels to renewable energy sources (RES) for electricity production (Wang et al., 2018a). The recent advancements in technology promise the potential to harness the RES for clean and abundant electricity generation. Among various renewable energy resources, solar energy is emerging as a promising resource for power generation (Şen, 2004). Solar energy is one of the most abundant energy resources. The average solar irradiance received on Earth's surface is approximately 1367 W/m^2, which can produce 1.74×10^{17} W in one year. Such a pervasive and massive amount of solar energy is sufficient to fulfill all power necessities worldwide. Fig. 1 represents the distribution of solar potential across the globe, indicating that the Earth offers overwhelming opportunities to harness solar energy. In this way, solar energy is considered the best substitute for conventional energy sources for solar photovoltaic (PV) power generation to fulfill industrial, commercial, and residential requirements. In recent years, the installation of PV power plants has been increased across the globe. According to a report, the worldwide PV power production showed an increment of 50% in 2016 compared to 2015, which amounts to 75 GW. Moreover, the developing countries are primarily encouraged by providing subsidized

* Corresponding author.
E-mail address: pratimatomar93@gmail.com (P. Kumari).

https://doi.org/10.1016/j.jclepro.2021.128566
Received 5 May 2021; Received in revised form 16 July 2021; Accepted 4 August 2021
Available online 11 August 2021

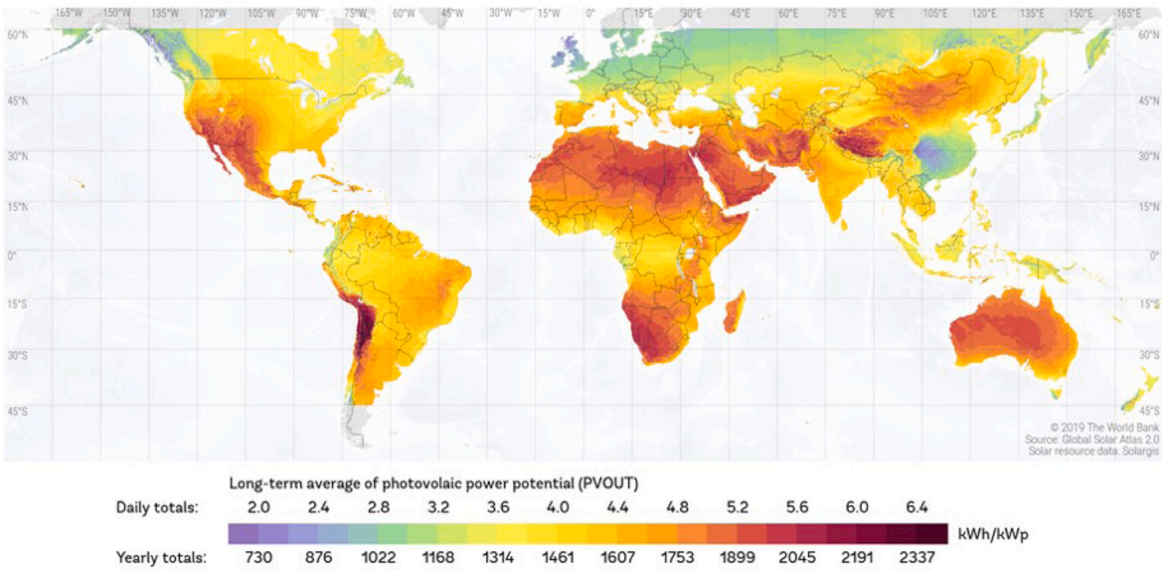

Fig. 1. The world solar resources map (SOLARGIS, 2019).

technology and tools for the installation of PV plants for electricity generation (see Fig. 2) .

Although solar energy is considered as the most promising alternative to fossil fuels by the industrial and scientific community, it brings along several threats to the reliable and stable integration of solar energy into the power grids (Espinar et al., 2010). For the successful functioning of a power plant, it is necessary to maintain a precise balance between the demand and supply of power. Based on these demand and supply predictions, plant authorities decide on the purchase of energy. The energy market follows a bidding culture, which implies that the larger error in the forecast means the larger energy cost Moreno-Munoz et al. (2008). The main challenge in the effective market penetration of solar energy is its highly volatile and intermittent nature. Therefore, precise forecasting of solar energy availability is highly desirable for the energy industry (Anderson and Leach, 2004). However, the solar energy companies cannot produce historical PV data required for energy predictions because of data privacy policies. In this case, global horizontal irradiance (GHI), an essential factor for solar power generation, is used to forecast solar energy. Solar irradiance data can be utilized for several solar energy applications, including plant installation, demand and supply balancing, load dispatch scheduling, storage management, trading of generated power in the market, etc. (Hammer et al., 1999; Frías-Paredes et al., 2017). However, due to high equipment cost, measured GHI data is not commonly available at most locations across the globe. For instance, in two highly populated countries, China and India, the number of meteorological stations, which provide physically measured GHI data is only 122 and 43, respectively (Zhang et al., 2017). GHI of a location depends on the climate and various meteorological parameters such as pressure, temperature, wind speed, relative humidity, sunshine duration, etc. Therefore, the meteorological parameters of a location can be utilized to forecast solar irradiance. Generally, the GHI data is predicted for different forecasting horizons according to the solar energy application that needs to be implemented, as shown in Fig. 3. For example, very short-term GHI prediction is used for monitoring the energy system. In contrast, long-term GHI prediction is desirable for site selection and installation of PV power plants (Coimbra et al., 2013). In recent years, GHI forecasting has drawn much attention from industries and researchers due to its important applications in the solar energy field. Researchers have conducted several comprehensive studies and reported many GHI forecasting models in the literature. GHI forecasting models can be categorized as empirical models, image-based models, statistical models and machine learning models (Voyant et al., 2017; Gueymard, 2012; Miller et al., 2018).

The empirical models use the geographical and measured meteorological parameters to model the solar irradiance data. Over the past few decades, several types of empirical models, such as temperature-based, cloudiness-based, sunshine-based, hybrid meteorological-based (uses multiple meteorological parameters) have been extensively applied to estimate GHI (Hassan et al., 2016). The first sunshine-based empirical model to estimate GHI was developed by Angstrom (1924), which was further modified by many researchers, including Samuel (1991), Ögelman et al. (1984), Badescu et al. (2013), Mecibah et al. (2014), etc. The existing studies suggest that sunshine-based model provides better results than other meteorological parameter-based empirical models as sunshine duration exhibits a strong relationship with solar irradiance data. However, the sunshine data is not readily accessible across the world. Therefore, researchers have proposed various temperature-based empirical models to estimate GHI. Temperature-based models have high applicability as temperature is the most commonly measured meteorological parameters. Hargreaves and Samani (1982) was the first to propose a temperature-based model, which employed minimum and maximum temperature as input parameters to estimate the GHI. Following this, Bristow and Campbell (1984) proposed a more advanced model, which modeled solar irradiance as an exponential function of diurnal temperature. Generally, temperature-based models were the most commonly used empirical model. However, they showed less accurate results. To further enhance the accuracy, other meteorological parameters, such as rainfall, relative humidity, pressure, were introduced to temperature-based models and named as hybrid models. The applicability of hybrid empirical models was limited due to the incorporation of too many meteorological parameters. Recently Chen et al. (2019a) reported various empirical models and recommended that empirical models are most suitable for long-term horizons (i.e., 6 to 72 h ahead) forecasting. These models include high calculation costs and therefore are not suitable for short-term horizon GHI prediction. Moreover, these models cannot capture the real-time cloud information and other meteorological parameters, which limits the preciseness of the GHI prediction models in noisy environments (Chen et al., 2019c; Yagli et al., 2019).

The image-based models use sky cameras or satellite images for GHI prediction. This approach shows promising performance in predicting solar irradiance for a large region (Hammer et al., 1999). Due to the high temporal and spatial resolution of sky images, cloud motion can

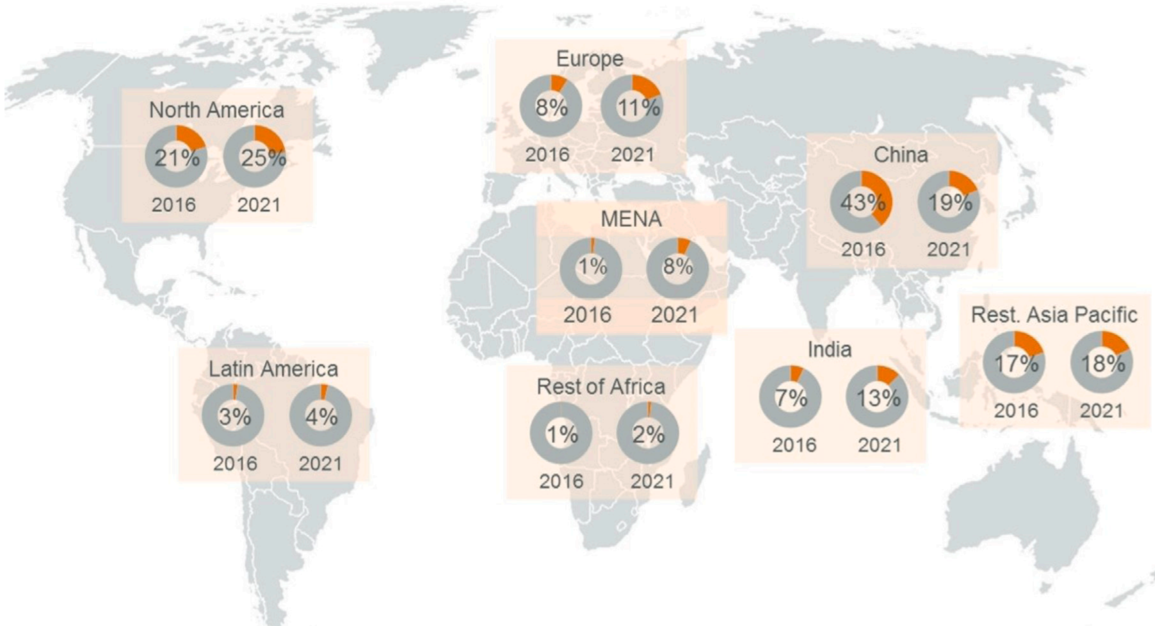

Fig. 2. A comparison of annual PV installation between 2016 and 2021 (APRICUM, 2016).

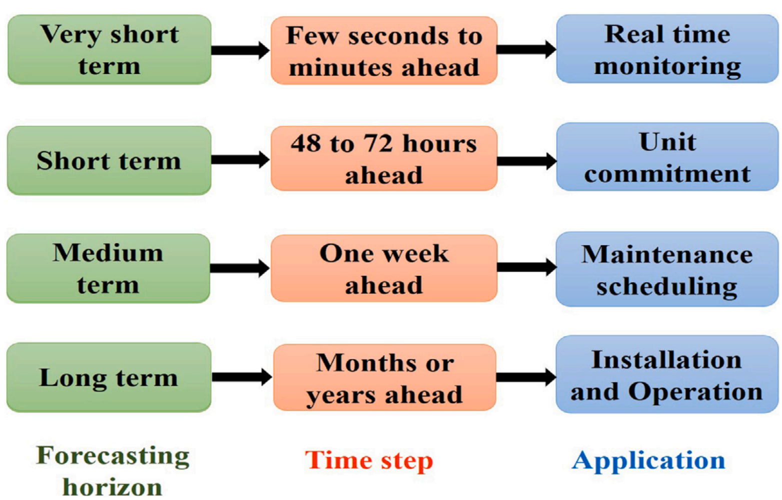

Fig. 3. Forecasting horizon and the time step with their applications (Kumari and Toshniwal, 2021a).

be captured. Unlike empirical models, image-based models capture the cloud information from the sky image dataset, which helps in accurate GHI forecasting. GHI prediction using satellite images has been recognized as a powerful approach. However, it faces few issues such as image dataset availability, expensive image capturing instruments, image processing, etc., which make the image-based technique less popular for GHI prediction (Nonnenmacher and Coimbra, 2014).

In contrast to the approaches mentioned above, statistical models use historical time series solar irradiance data to develop forecasting models. Statistical models construct a mathematical relationship using historical solar irradiance data. The most commonly available statistical models fall in the family of following three methods: autoregressive integrated moving average (ARIMA), exponential smoothing (ETS) and generalized autoregressive conditional heteroskedasticity (GARCH) (Reikard, 2009; Yang et al., 2012; Jaihuni et al., 2020). These models can be applied to forecast GHI for a horizon of 5 min - 6 h. Generally, statistical models perform well in predicting future values of stationary GHI time series. However, the time-series data of solar irradiance shows non-stationary behavior due to cloud and seasonal effects. Therefore, these models cannot capture non-linearity in data accurately and show low prediction performance (Sharma et al., 2016).

With the gradual emergence of artificial intelligence, machine learning methods have become most popular approach for solar irradiance forecasting. Machine learning methods follow the concept of learning patterns from the data, modeling parameters and building predictive models (Alsina et al., 2016). In this way, machine learning-based predictive models can extract highly complex and non-linear features from the data. In recent years, several machine learning techniques, including support vector machine (SVM), artificial neural network (ANN), random forest (RF), etc., have been intensively applied for solar irradiance prediction (Kumari and Toshniwal, 2020c; Alfadda et al., 2018). A detailed review of machine learning-based solar irradiance forecasting models is reported in Voyant et al. (2017). Machine learning methods also suffer from few limitations such as over-fitting, high computational cost, low performance in handling complex and high dimensional data (Ahmad et al., 2018). For instance, to achieve the highest possible performance, the machine learning models are generally over-tuned during the optimization of parameters. This leads to an over-fitting issue and low generalization of developed prediction models (Breiman et al., 1996). To further enhance the accuracy of GHI prediction models, an ensemble approach has been drawing attention in latest years. In this approach, multiple models are combined in order to integrate the benefits of different models (Opitz and Maclin, 1999). Several researchers have proposed various ensemble models for GHI forecasting. The advantage of employing an ensemble approach over simple machine learning methods is that the ensemble models can enhance the prediction accuracy by integrating the benefits of multiple models. Moreover, the ensemble approach produces more robust and stable GHI prediction models (Wang et al., 2018d).

The aforementioned machine learning methods for solar irradiance forecasting generally follow the core concept of shallow networks for the learning of models. These models are called shallow for the fact that they have one hidden layer or no hidden layer at all. Shallow models were introduced in 1980s to learn the patterns from the training data to make future predictions. The shallow models mainly include decision tree, support vector machine, simple neural networks, boosting, etc. Although shallow models have gained extensive attention in past years for several prediction applications, they also suffer from a few major drawbacks as follows. (a) First, detailed knowledge of the dataset associated with solar irradiance is required for the learning of a shallow network. The process of feature selection is quite tedious. Hence, it needs high expert skills for selecting appropriate input features to feed into the model, which makes shallow models unreliable and less self-reliant in extracting the inherent non-linear features for solar irradiance forecasting (Khodayar et al., 2017). (b) Shallow networks do not possess high generalization capability. Generally, shallow models show high performance in approximating the smooth target functions. However, solar irradiance data is highly intermittent and stochastic in nature, which adds noise to the forecasting target function and makes it non-smooth. Therefore, shallow models are less sufficient in learning complex patterns in solar irradiance data due to less generalization capability and suffer from the drawback of over-fitting, gradient disappearance and network training explosion (Bengio, 2009). (c) Shallow models show promising results when applied on relatively small datasets. However, in this era of big data, huge datasets are available to work on, which are collected from different sources such as meteorological sensors, remote meters and other latest technologies. Therefore, shallow models may suffer from instability issues and slow parameter convergence due to the huge size of data (Sun et al., 2016). Overall, the issues of tedious feature selection, over-fitting and high complexity in handling big data inspired the researchers to move towards a more advanced and promising approach of deep learning for GHI prediction.

In recent years, deep learning models have gained extensive attention as they perform well over conventional shallow models due to following three reasons: they can extract features automatically with no or little knowledge of background details, their strong generalization power and the ability to handle big data (Kawaguchi et al., 2017). The major difference between "shallow" and "deep" learning models is due to the number of times the input data experience the linear or non-linear transformation before reaching the output. Deep learning models have the advantage of transforming input data multiple times before producing the output, whereas shallow models transform the input data only one or two times (Khodayar and Wang, 2018). In this way, deep learning models can learn extremely complicated patterns from the data without much manual expertise and perform really well for several applications such as image processing, pattern extraction, classification and forecasting. For instance, Wang et al. (2020) applied deep learning models for building thermal load forecasting. Zhang et al. (2015) developed a deep model using Boltzmann machine for automatic extraction of features in a wind speed forecasting study. Pasupa and Sunhem (2016) compares the performance of a deep convolutional network and shallow models (ANN and SVM) for a case study of face shape dataset. Li et al. (2018b) developed a deep learning model for short-term wave energy prediction. Similarly, deep learning models have forecasting applications in various renewable energy domains, including wind speed (Hu et al., 2016), photovoltaic power (Mishra et al., 2020), solar irradiance (Qing and Niu, 2018), etc. Statistics reveal that several researchers have proposed deep learning-based forecasting models for different renewable energy resources, especially for solar irradiance forecasting (Kumari and Toshniwal, 2021b). However, there is no single article that has reviewed the existing deep learning-based studies for solar irradiance forecasting. Moreover, solar energy, being the most popular resource among various renewable energy sources, has several review papers published in recent times. For example, Yadav and Chandel (2014) provided an extensive review of ANN-based techniques for solar radiation prediction. Similarly, Pazikadin et al. (2020) reviewed the 87 articles that employ ANN for solar power forecasting. Voyant et al. (2017) reported an extensive review of various machine learning-based solar radiation forecasting models. Zendehboudi et al. (2018) published a review of SVM application for solar irradiance prediction. Recently, Antonanzas-Torres et al. (2019) reviewed the seventy clear-sky solar irradiance models in their study. Similarly, Zhang et al. (2017) presented a critical review of various physical models applied for solar irradiance estimation. In this way, many studies that review various types of irradiance forecasting models are available in the literature, but none of them reviewed the solar irradiance forecasting models from the perspective of deep learning.

This review study intents to fill several discussed research gaps systematically in several sections to provide the readers with a comprehensive knowledge about several aspects of the solar irradiance forecasting from the viewpoint of the deep learning based models, as shown in Fig. 4. A description of major factors, which influence the solar irradiance forecast, including forecasting horizon, weather classification, etc., is provided. The basic structure of the several well known deep learning models, including long short term memory (LSTM), deep belief network (DBN), convolutional neural network (CNN), echo state network (ESN), recurrent neural network (RNN) and gated recurrent unit (GRU), along with their application for solar irradiance forecasting have been summarized. To the best of our knowledge, no studies have been found in literature, which provides a comprehensive review of the application of deep learning techniques in the domain of solar irradiance forecasting. The paper is structured as follows: Few major factors which influence the accuracy of solar forecasting models are described in Section 2. Section 3 provides the introduction and working of the prevalent deep learning techniques. The detailed review of previous literature is discussed in Section 4. Finally, the conclusion and future prospects of present study are provided in Section 6.

2. Factors influencing the solar irradiance forecast

Solar irradiance forecasting is a sophisticated procedure, which is influenced by various factors, including forecasting horizon, weather type, performance evaluation metrics, etc. In this section, a detailed discussion of such factors is provided.

2.1. Forecasting horizons

The forecasting horizon can be defined as the time period in future for which forecasting has to be done. It can also be described as the time span between the actual time and the time for which a prediction is made. Generally, forecasting horizons are divided into three categories: short-term, medium-term and long-term. Few researchers have introduced a fourth category of forecasting horizons known as "very short-term forecasting". However, there is no universal classification of forecasting horizons has been introduced yet. However, it is necessary to know the future demand for electricity production and consumption by an electrical energy operator (Fig. 5). Based on the type of forecasting horizons, solar irradiance forecasting can be utilized for the implementation of different applications for the successful and efficient execution of PV power plants.

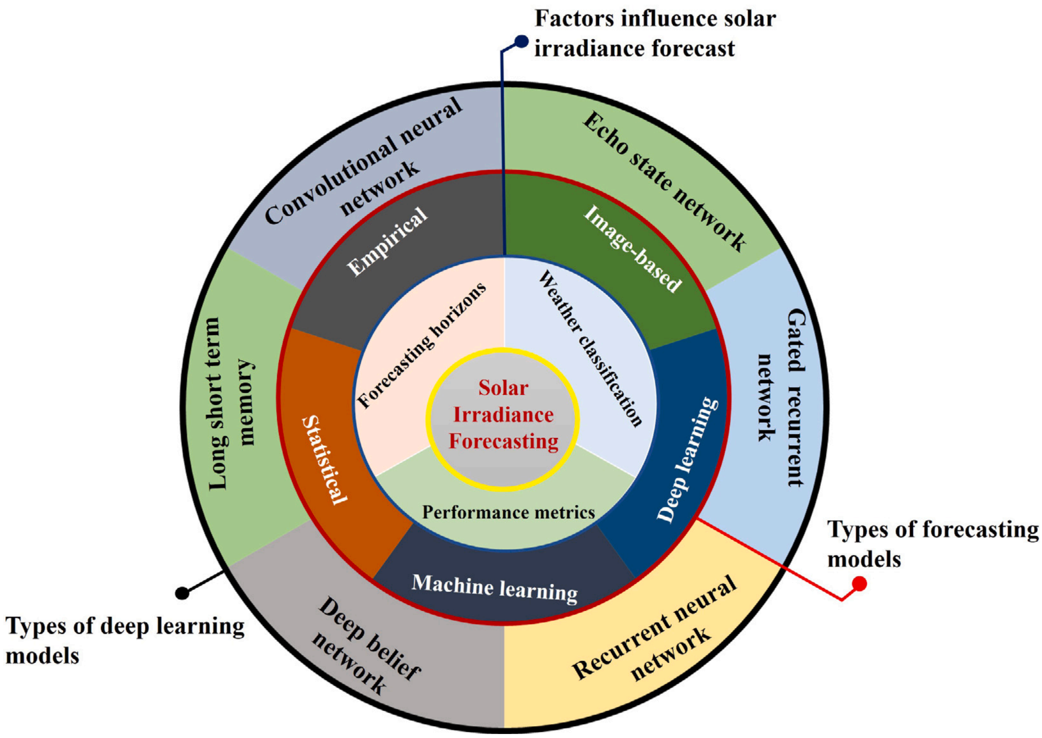

Fig. 4. Schematic illustration of the major topics (related to solar irradiance forecasting) discussed in present article.

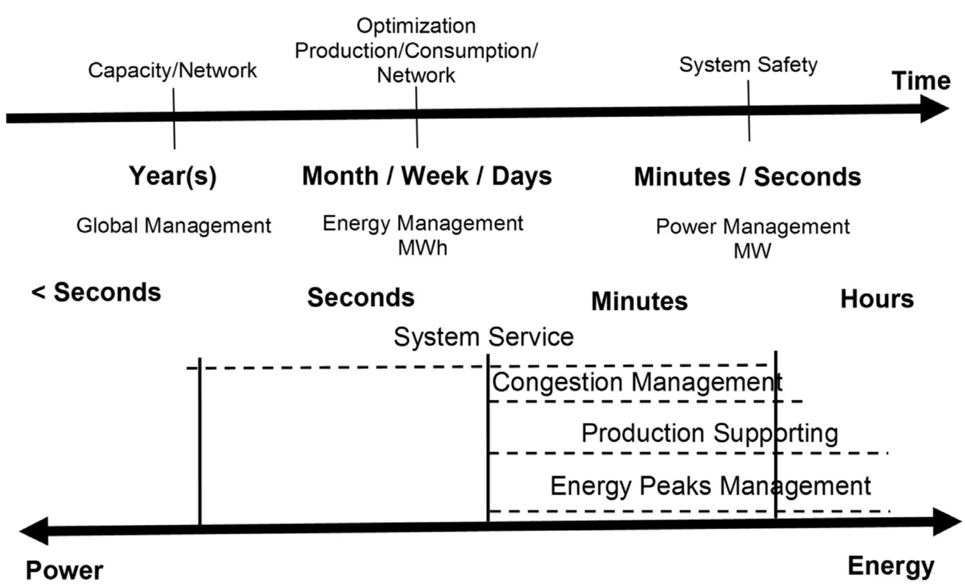

Fig. 5. Forecasting horizon for management of an electrical system (Notton et al., 2018).

2.1.1. Very short-term forecasting

Very short-term forecasting represents a prediction time period from 5 min up to 6 h (Reikard, 2009). For example, Yang et al. (2015) performed solar irradiance forecasting for a very short-term horizon using time-series irradiance data recorded every second. Few researchers have considered a time scale of few seconds to few minutes or up to a few hours under this category (Chow et al., 2011). Very short-term solar irradiance forecasting is highly usable in the pricing of electricity, bidding, real-time dispatch monitoring of power system and peak load matching (Engerer, 2015).

2.1.2. Short-term forecasting

Short-term forecasting has high applicability in managing the electricity market. It helps in power supply and demand balancing, load dispatch decisions, unit commitment, transaction planning in the electricity market, bulk energy storage, etc. (Ibrahim and Khatib, 2017). Generally, the short-term horizon span from 30 min to 72 h (Kalogirou, 2001). However, few researchers consider from 1 h to several hours, days or up to 7 days under this type. For instance, Jiang et al. (2017) proposed a solar irradiance forecasting model for 5 days ahead forecasting for maintaining the stability and efficient balancing between the supply and demand when integrating the solar power to the entire power system.

2.1.3. Medium-term forecasting

The temporal horizon considered for medium-term forecasting varies from few days, few weeks and up to a few months ahead (Olatomiwa et al., 2015). This category of forecasting horizon is necessary for designing the maintenance schedule of solar power plants comprised of transformers and other machinery in such a way that it incurs minimum loss (Heng et al., 2017).

2.1.4. Long term forecasting

Generally, researchers consider a period of few months to years under long-term forecasting scenarios (Mishra et al., 2008). This type of prediction horizon is highly suitable for designing long-term plans for the successful execution of solar power plants. Long-term forecasting model helps in global management such as site selection to establish a PV power plant, transmission, operation and distribution of solar energy (Kaushika et al., 2014). However, forecasting for long horizons is less accurate as it cannot predict weather fluctuations in such a long time span. Yet several researchers have performed long-term forecasting models to design scheduling plans, pricing and site selection (Jiang, 2008; Hong et al., 2013).

2.2. Influence of forecasting horizon on solar irradiance prediction accuracy

The forecasting horizon is one of the most influential parameters which affect prediction accuracy. It has been reported that keeping the prediction model, its parameters, input variables same, the accuracy of prediction model changes with the change in forecasting horizon (Perez et al., 2010). Researchers have applied several types of models to perform multi-step solar irradiance forecasting with different forecasting horizons. Guermoui et al. (2018) predicted for a horizon ranging from 1 to 10 steps ahead, while Long et al. (2014) predicted for a horizon ranging from 1 to 3 days in daily increment. The findings of the study suggested that the value of RMSE has increased with the increment in the forecast horizon's duration.

Sun et al. (2018) applied an ensemble learning model based on decomposition clustering (DCE) for solar radiation forecasting. This framework employs least square support vector regression (LSSVR) optimized by gravitational search algorithm (GSA) for model development. The obtained prediction results suggest that the ensemble models perform better than single models. Moreover, the prediction accuracy of developed models is evaluated for different m-steps ahead forecasting horizons (m=1, 3 and 6). It has been found that the prediction accuracy of forecasting models (both single and ensemble) reduces with the increment in forecasting horizon, as shown in Fig. 6. Huang et al. (2018) proposed a solar irradiance forecasting model for a forecasting horizon range of 30–120 min, and they reported that the model's performance changes with the forecasting horizon variation. Similarly, Li et al. (2016) developed a very short-term forecasting model using SVM. They found that the prediction accuracy dropped 96% to 64.6% for a forecasting horizon range of 5-min to 30-min for the same dataset. It can be ascertained that the shorter time scale of training data as compared to the testing data does not enhance the prediction accuracy of the model. The increased statistical information for shorter time scales does not contribute to the accuracy but complicates the training process. The solar irradiance forecasting accuracy is affected by many inter-dependent factors. For example, cloud conditions critically affect the amount and intensity of solar radiation that reaches the surface of the Earth, especially in very short-term horizons or on seconds or minute scale. Therefore, the need to classify and predict the cloud conditions is highly desirable for accurate solar forecasting. Many researchers did not consider cloud conditions during model development, which lead to reduced prediction performance, specifically on cloudy times (Dong et al., 2015; Royer et al., 2016; Wang et al., 2018c).

The above discussion leads to a conclusion that with the increased forecasting horizon, the solar irradiance forecasting accuracy decreases. This is due to the cloud conditions and weather that cannot be predicted accurately for longer horizons due to its intrinsic stochastic behavior. In addition, the short-term solar irradiance forecasting is more relevant for PV power prediction, while long-term horizon is more preferable for planning and installation of the power system. Therefore, this review paper focuses on the researchers that are more inclined towards contributing to the enhancement of short-term solar irradiance forecasting models.

2.3. Weather classification

Solar radiation is a highly influential parameter in determining the PV power potential of a solar plant. The availability of solar irradiance depends on several meteorological variables, including temperature, pressure, relative humidity, aerosol index, wind speed and cloud cover. Thus, the accuracy of solar irradiance forecasting models is severely affected by the weather change of a location. This suggests that weather classification is essential to enhance the predictive performance and robustness of a forecasting model. Many researchers have demonstrated that weather classification is a fundamental part of pre-processing for short-term solar irradiance forecast (Bae et al., 2016; Yu et al., 2019; Kwon et al., 2019).

The insufficient data for the models' training is the biggest challenge in weather classification-based solar irradiance forecasting. For instance, 33 weather types are reported in Wang et al. (2015, 2019b), which are further distributed into 10 weather classes by merging few types of weathers into single. To resolve this, most of the researcher have classified weather into three or four types (Wang et al., 2018e; Akarslan et al., 2018). For instance, McCandless et al. (2016) applied K-means clustering on surface weather and irradiance data to identify the different cloud regimes. Further, regime-dependent ANN models are applied for irradiance prediction that has improved the forecast precision. Few researchers applied self-organizing maps (SOM) for partitioning the meteorological input data into several disjoint groups and developed forecasting models for each disjoint group (Dong et al., 2015; Wang et al., 2019c). Similarly, based on solar irradiance features, Wang et al. (2015) constituted four general weather classes that cover each weather type. Lima et al. (2016) applied Weather Research and Forecasting Model (WRF) along with ANN for solar irradiance forecasting in the Northeastern Brazilian region. They formed clusters to identify the homogeneous climatic regions and classified the data into two typical climate seasons: dry and rainy. Overall, the existing literature suggests that the weather classification is one of the most influential factors in enhancing the predictive performance of solar irradiance forecasting models, necessitating the inclusion of weather types during forecasting (Engerer, 2015; Wang et al., 2018f; Nann and Riordan, 1991).

2.4. Forecast model performance

Performance evaluation is a way of measuring how good something is. The performance evaluation is beneficial in various stages of model development. For example, assessment during the training of the model or while judging the performance of the model on unseen conditions/data or comparison of models. However, performance comparison is not simple as it is influenced by various factors, such as forecasting horizon, model parameters, variation in climatic conditions according to the site. The performance evaluation in case of solar irradiance forecasting works by comparing the actual solar irradiance and predicted solar irradiance. The most commonly used statistical measures for performance evaluation of a prediction model are as follows:

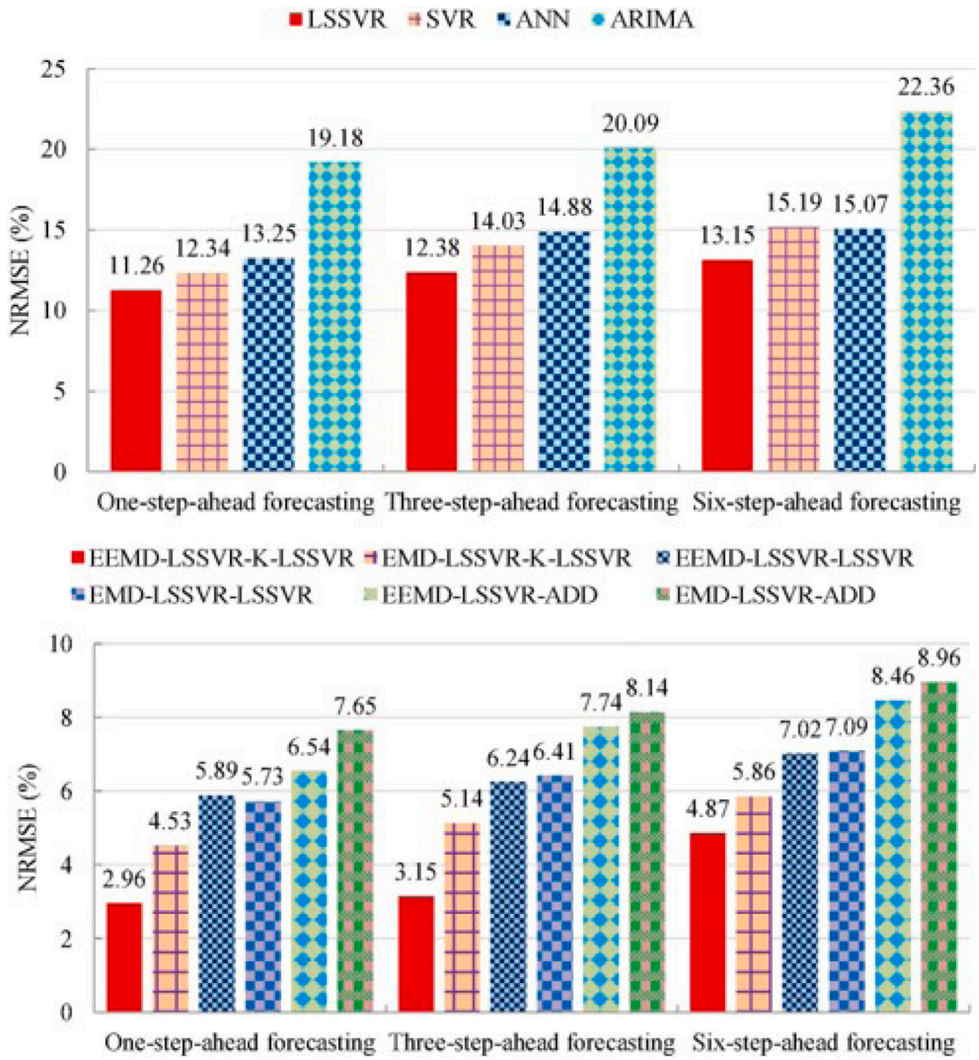

Fig. 6. Prediction performance of single models and ensemble models against different time steps (Sun et al., 2018).

- **Mean bias error (MBE)**: It demonstrates the mean bias of the forecasting model:

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i) \tag{1}$$

where y_i is the actual solar irradiance, $\hat{y}$ is the predicted solar irradiance, N is the total number of observations. The MBE compensates the error by canceling the positive from negative. Therefore, it is not a reliable mode of performance evaluation. However, it gives a good idea about how much a model overestimates or underestimates (Dahmani et al., 2014).

- **Mean absolute error (MAE)**: It is determined by calculating the average of the absolute difference between actual and predicted solar irradiance values. In this way, it gives equal weight to all discrepancies in the data (Aguiar et al., 2016).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \tag{2}$$

- **Mean square error (MSE)**: It is calculated by squaring the difference of the actual and predicted solar irradiance values. This metrics penalizes the higher differences (Kumari and Wadhvani, 2018).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 \tag{3}$$

- **Root mean square error (RMSE)**: It is calculated by taking the square root of the average of the squared differences of actual and predicted solar irradiance values. RMSE is known as the most reliable and appreciated performance evaluation metrics as it helps in identifying and eliminating the outliers in the data (Gutierrez-Corea et al., 2016).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{4}$$

- **Mean absolute percentage error (MAPE)**: MAPE is similar to MAE but the difference between each actual and predicted observation is divided by the actual observed value to determine the relative gap (Ozgoren et al., 2012).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{5}$$

- **Normalized RMSE (nRMSE)**: Generally, nRMSE is calculated for larger datasets to determine the overall deviations (Fernández-Peruchena et al., 2015).

$$nRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}}{\bar{y}} \tag{6}$$

where $\bar{y}$ denotes the mean of the actual solar irradiance.

- **Correlation coefficient (R)**: It represents the measure of the strength of the linear relationship between actual and predicted solar irradiance (Shaddel et al., 2016).

$$R = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}} \tag{7}$$

- **Forecast skill score (FS)**: FS score represents the performance comparison of a model to a benchmark or reference model, calculated as follows:

$$FS = 1 - \frac{RMSE_{Forecast\_model}}{RMSE_{Benchmark\_model}} \tag{8}$$

A perfect forecast model will result in a FS score of 1. A model having forecast error equal to the benchmark model will have 0 FS score while a forecast with higher forecast error will leads to a negative FS score (Yagli et al., 2019).

3. Basic structure of deep learning methods

The basic structures of the most popular deep learning models, which are highly recommended for solar irradiance foresting, are discussed in this section. Generally, long short-term memory (LSTM), deep belief network (DBN), convolutional neural network (CNN), echo state network (ESN), recurrent neural network (RNN), gated recurrent unit (GRU), and their hybrids are frequently applied in the literature. The necessary details about the structures and training mechanism of these models are discussed below.

3.1. Convolutional neural network

In the late 1980s, LeCun proposed the CNN model, which is known as one of the most popular deep neural networks. The architecture of a CNN is comprised of various layers, namely convolutional layer, pooling layer, and fully connected layer, as shown in Fig. 7.

The convolutional layer is the most fundamental element in the CNN architecture, which helps in extracting the local features from the input data. It applies a linear convolution operation to the feature maps of the previous layer and applies a non-linear activation function to get the output feature maps. The convolutional layer's operation can be demonstrated as follows:

$$x_p^m = f(\sum_{q \in N_p} x_q^{m-1} * k_{qp}^m + b_j^m), \tag{9}$$

where x_j^m represents the jth output feature map of the mth layer, x_q^{m-1} represents the qth output feature map of the $m-1$th layer, k_{qp}^m denotes the weight between qth input and pth output map, N_p represents the input maps selection, $*$ denotes the convolution operation, b_j^m denotes the bias and f denotes the activation function.

After convolutional layer, pooling layer is encountered in the CNN architecture. Pooling layer performs a downsampling operation which helps in reducing the dimension of the feature maps. Generally, the average (Average pooling) or maximum (maximum pooling) value of a feature map is calculated to realize the pooling layer's operation, as shown below:

$$x_p^m = f(\beta_p^m down(x_p^{m-1}) + b_p^m), \tag{10}$$

where $down(\cdot)$ demonstrates the pooling function, x_p^{m-1} demonstrates the pth input feature map of the mth layer, β_p^m denotes the bias.

Once the convolutional layer extracts the features, which are further downsampled by the pooling layer. Finally, they are transferred to a fully connected layer, which determines the final output as shown below:

$$x^m = f(K^m x^{m-1} + b^m), \tag{11}$$

where x^m demonstrates the final output vector, K^m demonstrates the weight between the mth and $m-1$th layer and b^m demonstrates the bias.

3.2. Deep belief network (DBN)

A deep belief network (DBN) was initially introduced by Geoffrey Hinton in 2006 and has been used in various domains (Hinton et al., 2006). DBNs can be viewed as a probabilistic generative graphical model that uses probabilities and unsupervised learning to build the models. They overcome several limitations of traditional neural networks such as slow convergence and learning rate, local minima due to inadequate parameter selection, etc. A DBN is a deep learning network developed by stacking several Restricted Boltzmann Machine (RBM) together, as shown in Fig. 8. Each RBM in the DBN network is consists of two layers: visible (v_i) and hidden layer (h_i). In DBN design, the hidden layer of each RBM serves as a visible layer of the next RBM. The architecture of a DBN has bidirectional and symmetrical connections between different layers. The two uppermost layers have undirected connections, which constitutes an associative memory, while the bottom layers have directed connections. The training of a DBN model is performed by a greedy learning approach, i.e., train one layer at a time to obtain a global optimum. The training process starts from the bottom layer or the visible layer of the RBM, which is further processed by the hidden layer. The hidden layer learns the features and these output features are given as input to the subsequent RBM stage. This learning process repeats until the top of the stacked RBMs is reached and a final optimized model is obtained. The use of a greedy learning algorithm to train the network is beneficial in many ways: first, it helps in optimizing the weights at each layer. Second, it helps in proper initializing of the network, which avoids the problem of local minima trap. In addition, the greedy learning algorithm makes the training process fast and efficient (Chen et al., 2015). The main disadvantage of using DBNs is that building a DBN architecture is computationally expensive as it involves the training of several RBMs (Lee et al., 2007).

3.3. Recurrent neural network (RNN)

Recurrent neural network (RNN) is a class of artificial neural networks specially designed to model sequential or time-series data. Time-series data contains intrinsic temporal information, which cannot be captured by simple neural network (Hüsken and Stagge, 2003). In contrast to a simple neural network, RNNs are strengthened by an additional time-step edge which introduces an idea of time to the neural network (Yu et al., 2018). The edges named as recurrent edges connect the adjacent stages to form a cycle of self-connections of a neuron to itself (Rahman et al., 2018). These self-connected loops represent the different time steps. Fig. 9 illustrates a basic architecture of a recurrent unit. A hidden state vector (h_t) set as zero at the initial stage is connected to every hidden unit. It has the same length as the number of inputs and stores the useful information observed in the past. The hidden state at t instance uses the feedback connections to recall the hidden state vector at $t-1$ time instance. In this way, the hidden state vector at previous time instance along with the current input (x_t) is used to calculate the hidden state at t time instance. Consequently, the final output (y_t) is influenced by both, current input as well previously stored information. Following equations represent the process mathematically:

$$h_t = f(W_{hx}x_t + W_{hh}h_{t-1} + B_h) \tag{12}$$

$$\hat{y}_t = f(W_{yh}h_t + B_y) \tag{13}$$

where $f(\cdot)$ represents an activation function, W_{hx} and W_{hh} represents the weight matrix between input and a hidden layer and hidden layer and itself at previous time steps, respectively. B_h and B_y represents the bias vector.

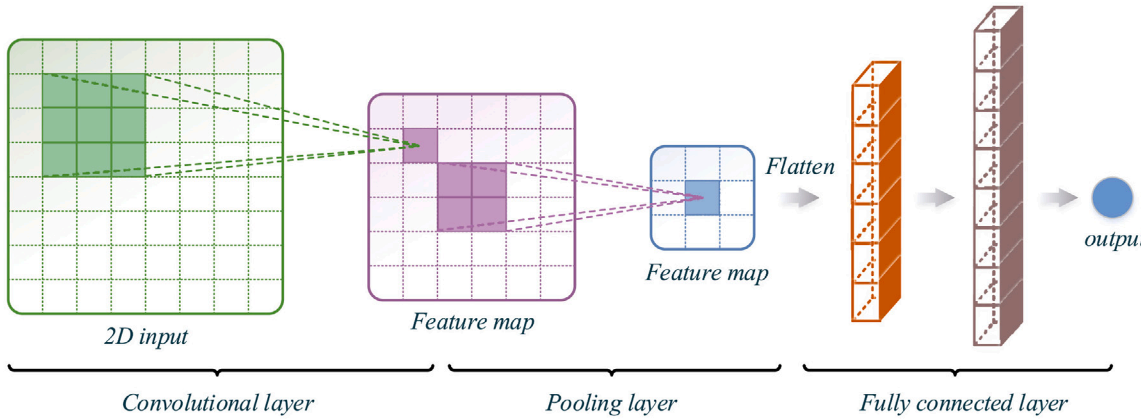

Fig. 7. The basic architecture of Convolutional neural network (CNN) (Zang et al., 2020b).

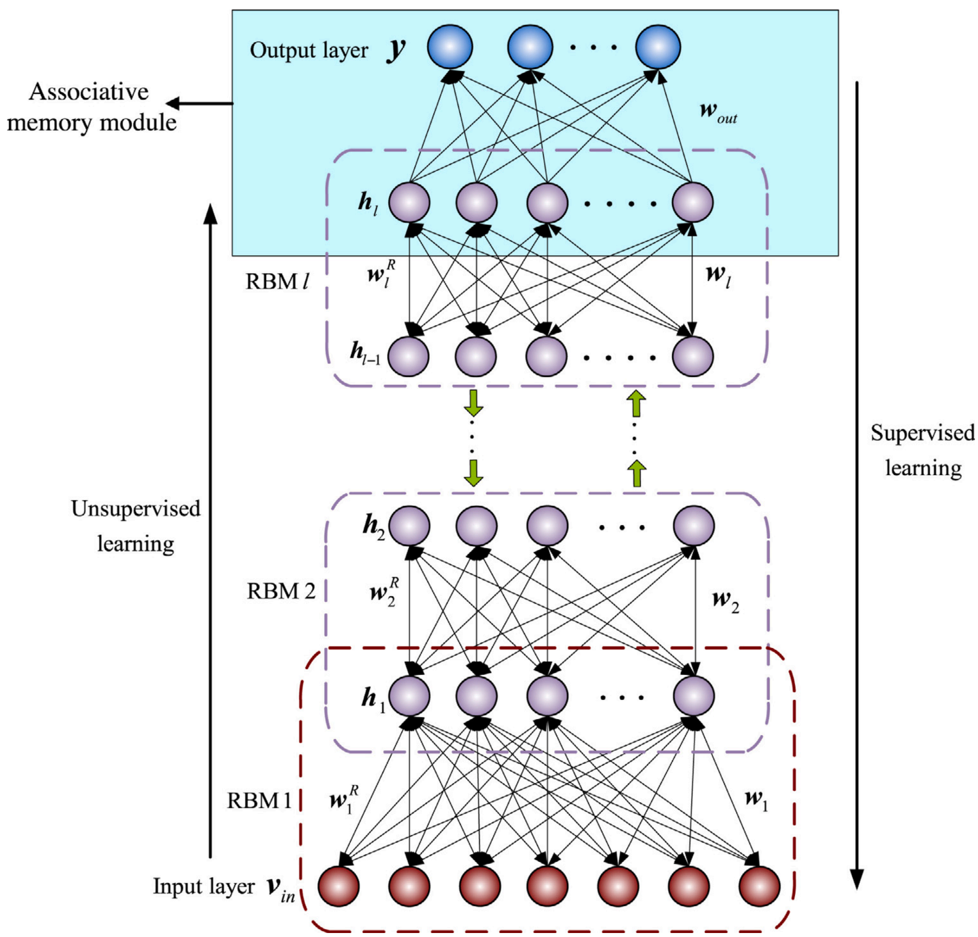

Fig. 8. The structural diagram of Deep belief network (DBN) (Qiao et al., 2018).

3.4. Long short term memory (LSTM)

LSTM network can be described as an extension and enhanced version of recurrent neural networks (RNNs) that has been successfully applied in time series prediction problems. It has been reported that RNN networks are incapable of handling long-term dependencies in data due to vanishing gradient and gradient explosion problem (Bandara et al., 2017). However, this issue has been resolved with the introduction of LSTM networks introduced by Sepp Hochreiter and Jürgen Schmidhuber (Qing and Niu, 2018). The architecture of LSTM addresses the issue of vanishing gradient by incorporating the memory cells and gates, which regulate the information flow in the network. Fig. 10 shows the basic architecture of a LSTM cell and information dissemination in LSTM network. It contains following gates: forget gate (f_t), input gate (i_t), update gate (g_t) and output gate (o_t). The mathematical expressions to represent their working are given below. Please note that w_f, w_i, w_g and w_o represents the weight matrices of the forget, input, update and output gate, respectively, b_f, b_i, b_g and b_o represents the biases of the forget, input, update and output gate, respectively. σ demonstrates the sigmoid activation function.

The forget gate is the main element of the LSTM architecture. It controls the information needs to be removed from the memory cell.

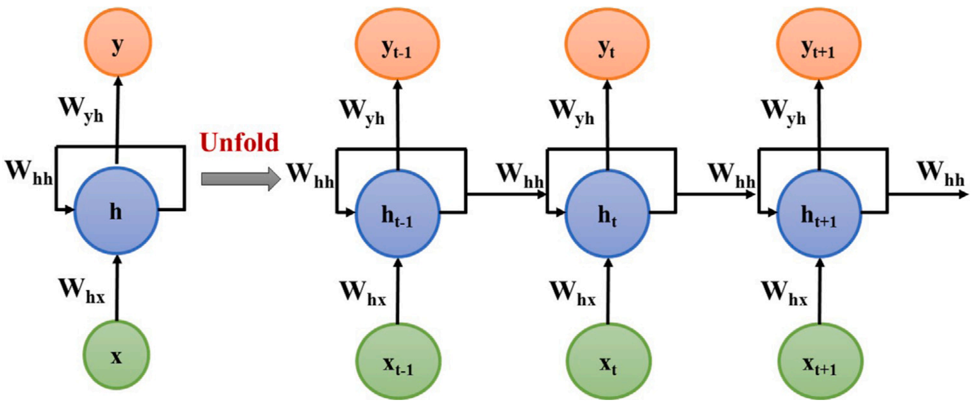

Fig. 9. A folded and unfolded architecture of Recurrent neural network (RNN).

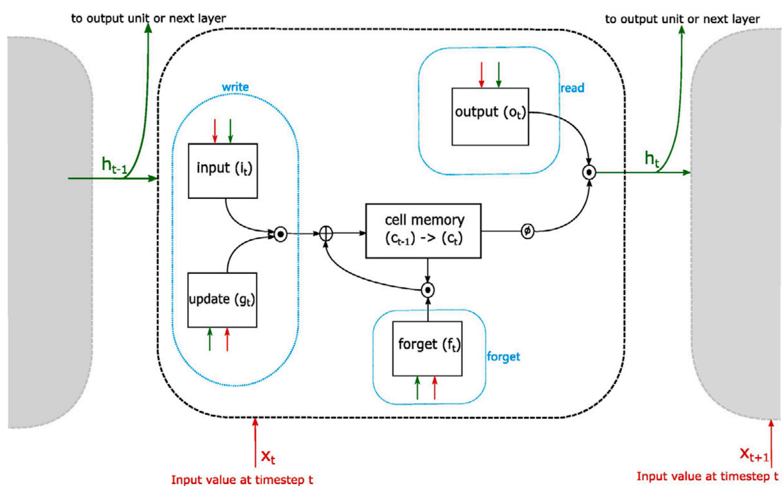

Fig. 10. Basic architecture representing the information dissemination in Long short-term memory (LSTM) (Srivastava and Lessmann, 2018).

Forget gate applies a sigmoid function on the output of the last state (h_{t-1}) and input data (x_t):

$$f_t = \sigma(w_f.[h_{t-1}, x_t] + b_f) \tag{14}$$

The input gate uses sigmoid function (σ) to decide which values to write, while update gate uses *tanh* activation function to create new cell values, as shown below.

$$i_t = \sigma(w_i.[h_{t-1}, x_t] + b_i) \tag{15}$$

$$g_t = tanh(w_g.[h_{t-1}, x_t] + b_g) \tag{16}$$

The previous cell state (C_{t-1}) with forget gate interacts with update gate to update the new cell state (C_t) as given:

$$C_t = f_t * C_{t-1} + i_t * g_t \tag{17}$$

Finally, output gate regulates the output of a cell. The output gate is combined with a cell state, which is activated by *tanh* function to get the final output, h_t as given:

$$o_t = \sigma(w_o.[h_{t-1}, x_t] + b_o) \tag{18}$$

$$h_t = o_t.tanh(C_t) \tag{19}$$

3.5. Gated recurrent unit (GRU)

Gated recurrent unit (GRU) is one of the popular variants of RNNs, which is introduced by Cho et al. (2014). GRU aims to address the vanishing gradient problem of basic RNN and can learn long-term dependencies in data. GRU can also be considered as a variant of LSTM as both have similar working mechanisms and designs. Similar to LSTM, GRU employs a gating mechanism to handle the flow of information. In GRUs, the input and forget gate are merged into a single update gate. Unlike LSTM, GRU contains only two gates: update gate (z_t) and a reset gate (r_t). These two gates decide the useful information that should be retained from the past and the irrelevant information which should be removed. The mathematical expressions to explain the working mechanism of a GRU are described as follows. Initially, the update gate is used to decide what information needs to preserved for the future, and calculated at time t as follows:

$$z_t = \sigma(w_z x_t + u_z h_{t-1}) \tag{20}$$

where σ is the sigmoid activation function, x_t is the input to the model, w_z and u_z are the weight matrices and h_{t-1} carries the information from the previous time step ($t-1$). Further, reset gate decides how much of the past information has to be forgotten, as follows:

$$r_t = \sigma(w_r x_t + u_r h_{t-1}) \tag{21}$$

Next, a new memory content (h') is generated using reset gate (r_t) as given below:

$$h' = tanh(W x_t + r_t \odot U h_{t-1}) \tag{22}$$

where W and U represents the weight matrix between input to hidden and hidden to hidden layer, respectively. An Hadamard (element-wise) product is calculated between (r_t) and $U h_{t-1}$. Finally, the current state hidden value is calculated using update gate as shown below:

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h' \tag{23}$$

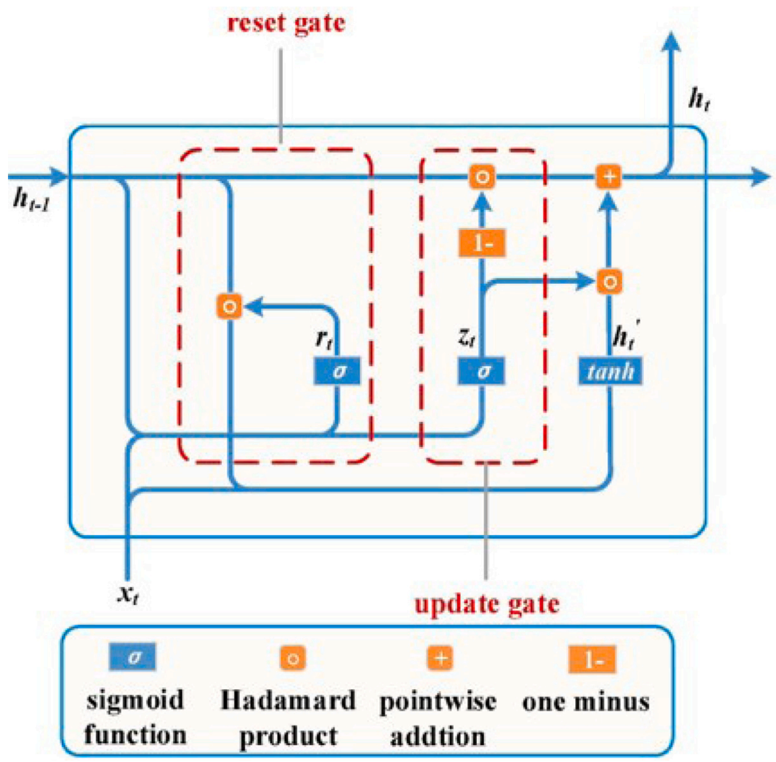

Fig. 11. Basic structure of a Gated recurrent unit (GRU) (Liu et al., 2019).

Although, GRUs are said to be similar to LSTM, formers have few advantages. The architecture of GRU is less complicated than LSTM, as GRUs have less variables than LSTM (see Fig. 11), which makes them more effective and compact (Chen et al., 2019b).

3.6. Echo state network (ESN)

Echo state networks (ESNs), introduced by Jaeger and Haas in 2004, are a special type of RNNs that use reservoir computing framework (Jaeger and Haas, 2004). The ESN networks have surprising capabilities in modeling chaotic and non-linear systems. ESN is preferred over simple neural networks due to following reasons. First, the ESN remembers the past information in such a way that it prioritizes the most recent information and forgets with the delay time. Second, the training procedure of an ESN is relatively simple, even then, they are known as universal function approximators. Third, in solving the complex time series prediction problems, ESN shows higher performance as compared to traditional neural networks. In this way, ESN has been utilized in many domains such as stock price prediction (Lin et al., 2009), robot control (Ishii et al., 2004), standard Mackey–Glass series prediction problem (Jaeger, 2001; Jaeger and Haas, 2004), etc.

A typical ESN is comprised of three parts: input layer having K units (left part), internal dynamic reservoir with N units (middle part) and output layer having L units (right part), as illustrated in Fig. 12. All the input layer nodes have connections with all nodes in the internal layer and all the nodes in the internal layer are linked to all nodes of the output layer. The internal layer or the dynamic reservoir has a large number of nodes that are sparsely connected to each other (typically 1% connectivity) (Jaeger, 2007). In this way, four weight matrices are generated in an ESN architecture: W^{in}, W, W^{out} and W^{back} which represents the weights for the input, internal, output connections and for the connections from output units to internal units, respectively. Moreover, the activation function of input, internal, output units and noise at time instance t is represented as $u(t)$, $x(t)$, $v(t)$ and $n(t)$. The activation of internal units $x(t+1)$ at time instance $t+1$ is updated as:

$$x(t+1) = f(W^{in}u(t+1) + Wx(t) + W^{back}v(t) + n(t+1)) \tag{24}$$

where f represents the output function of internal unit, which is generally a sigmoid function. The output is calculated as follows:

$$\hat{v}(t+1) = f^{out}(W^{out}x(t+1)) \tag{25}$$

where f^{out} represents the output function of output unit. It must be noted that training of an ESN is performed in such a way that the weight of the W^{in}, W and W^{back} are initialized in the beginning with some random values. The elements of W^{out} matrix are the only trainable weights.

The internal weight matrix (W) spectral radius should be less than 1, which means that final internal weight matrix must be normalized as follows:

$$W = a\left(\frac{W}{|\lambda_{max}|}\right) \tag{26}$$

where a represents a scaling parameter with a value between 0 and 1 and $|\lambda_{max}|$ represents the spectral radius of W.

In the training process, the output matrix W^{out} is optimized in such a way that the training error is minimized. Let $v_{teach}(n) = (v_1(n), \ldots ..v_L(n))$ demonstrates the output teacher signal at n time step, and suppose $G_{teach} = (f_{out})^{-1}v_{teach}(t)$. Minimize the MSE vector (MSE_{train}) as follows:

$$MSE_{train} = \frac{\sum_{t=t_{min}}^{t_{max}}(G_{teach}(t) - W^{out}x_{teach}(t))^2}{t_{max} - t_{min}} \tag{27}$$

where t_{max} and t_{min} represents the lower and upper time step bound, respectively. $x_{teach}(t)$ represents the teacher signal vector.

3.7. Generalized adversarial networks (GAN)

A generative adversarial network (GAN) was first proposed by Ian Goodfellow in 2014 (Goodfellow et al., 2014). GANs process the training data to learn and discover patterns in it and generate new artificial data with similar characteristics and distribution. These artificial samples are utilized to create new data instances. GAN can be used for data augmentation when a large volume of dataset is

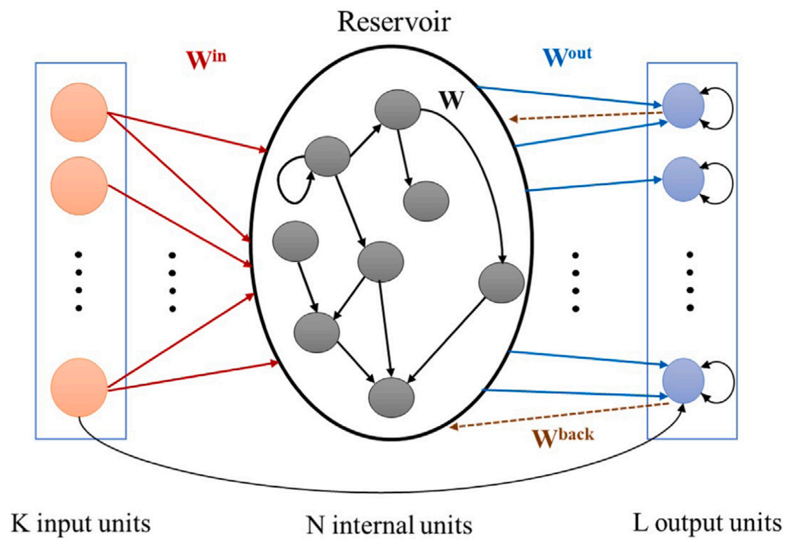

Fig. 12. Structural diagram of an Echo state network (ESN).

required. The architecture of a basic GAN is comprised of an NN-based generator (G) and an NN-based discriminator (D). These two neural networks are iteratively trained during which generator helps in generating the realistic fake samples until they are non-distinguishable from real data samples. A basic structure of GAN is represented in Fig. 13. The generator uses a random noise z from a given distribution $z \sim P_z$ (e.g., uniform or gaussian distribution) to generate a huge amount of synthetic data. The discriminator tries to differentiate the real or synthetic data. The discriminator loss is calculated to update the generator and discriminator.

Given a random noise z from a given distribution $z \sim P_z$ and a real sample x from a real data distribution $P_{data}(x)$. The discriminator output for real samples and generated samples are represented by $D(x)$ and $D(G(x))$, respectively. The generated output is represented by $G(z)$. The discriminator tries maximize the $log D(x)$ to 1 in order to improve its ability of identify the real sample whereas it identifies synthetic samples by maximizing the $log D(1 - D(G(z)))$ to 0. The generator minimizes the $log(1 - D(G(z)))$ in order to avoid the generation of samples which are easily distinguishable by discriminator.

The adversarial game between generator and discriminator can be presented as a min–max optimization task as shown below:

$$\min_{G} \max_{D} Q(D,G) = \mathbb{E}_{xP_{data}(x)}[log D(x)] + \mathbb{E}_{zP_z(z)}[log(1 - D(G(z)))] \tag{28}$$

where $Q(D,G)$ demonstrates the objective function, $\mathbb{E}_{xP_{data}(x)}$ and $\mathbb{E}_{zP_z(z)}$ demonstrates the expected loss for $log D(x)$ and $log(1 - D(G(z)))$, respectively.

In the training process of GAN, initially loss function is calculated and discriminator is updated as follows:

$$\bigtriangledown_{\theta_d} \frac{1}{n} \sum_{j=1}^{n} [log D(x^j) + log(1 - D(G(z^j)))] \tag{29}$$

where n is the batch size and j is the jth sample instance. The stochastic gradient $\bigtriangledown_{\theta_d}$ of discriminator is updated by ascending it.

Further, the generator is updated by descending its stochastic gradient $\bigtriangledown_{\theta_g}$ as given:

$$\bigtriangledown_{\theta_g} \frac{1}{n} \sum_{i=1}^{n} [log(1 - D(G(z^j)))] \tag{30}$$

3.8. Attention mechanism

Inspired by the human visual attention mechanism, Bahdanau et al. (2014) introduced attention mechanism for the first time in 2014. The attention mechanism simulates the behavior of brain by directing its focus to certain factors. Attention mechanism has been efficiently utilized in different domains such as image analysis (Song et al., 2018), video analysis (Li et al., 2018a), machine translation (Choi et al., 2018), etc., and achieved the best performance. In view of the higher performance and wide application of attention mechanism, researchers have begun to apply the attention mechanism in time-series forecasting domain.

The incorporation of attention mechanism in deep neural network allows to focus on the key part of the input data which is of more importance to the current output. For instance, in case of LSTM, the hidden layer output vector $H = h_1, h_2, ..h_n$ is given as input to the attention layer. The attention weights α_i for each h_i can be calculated as follows:

$$e_i = tanh(W_h h_i + b_h), e_i \in [-1, 1] \tag{31}$$

$$\alpha_i = \frac{exp(e_i)}{\sum_{i=1}^{n} exp(e_i)}, \sum_{i=1}^{n} \alpha_i = 1 \tag{32}$$

where W_h and h_i represents the weight matrix and bias. The attention vector $A' = a_1', a_2', \dots .a_n'$ is determined as follows:

$$a_i' = \alpha_i \cdot h_i \tag{33}$$

The attention mechanism helps in customizing an attention layer whose parameters are determined using an optimization algorithm. This attention layer helps the LSTM to incur higher performance by efficiently managing the long-term dependencies in the data.

3.9. Bidirectional RNN

In regular recurrent neural networks (RNN) the future input information cannot be provided to the current state due to which they have restrictions on the input data flexibility. To overcome the limitations of RNNs, a bidirectional recurrent neural network (BRNN) is introduced by Schuster and Paliwal (1997) in 1997. BRNNs have the capability to take the input from both forward and backward direction, i.e. BRNN can be trained with all information from past as well as future at a time step. The basic structure of the BRNN is shown in Fig. 14 and can be formulates as shown below:

$$\vec{h}_t = f(w_{x,\vec{h}} x_t + w_{\vec{h}\vec{h}} h_{t-1} + b_{\vec{h}}) \tag{34}$$

$$\overleftarrow{h}_t = f(w_{x,\overleftarrow{h}} x_t + w_{\overleftarrow{h}\overleftarrow{h}} h_{t+1} + b_{\overleftarrow{h}}) \tag{35}$$

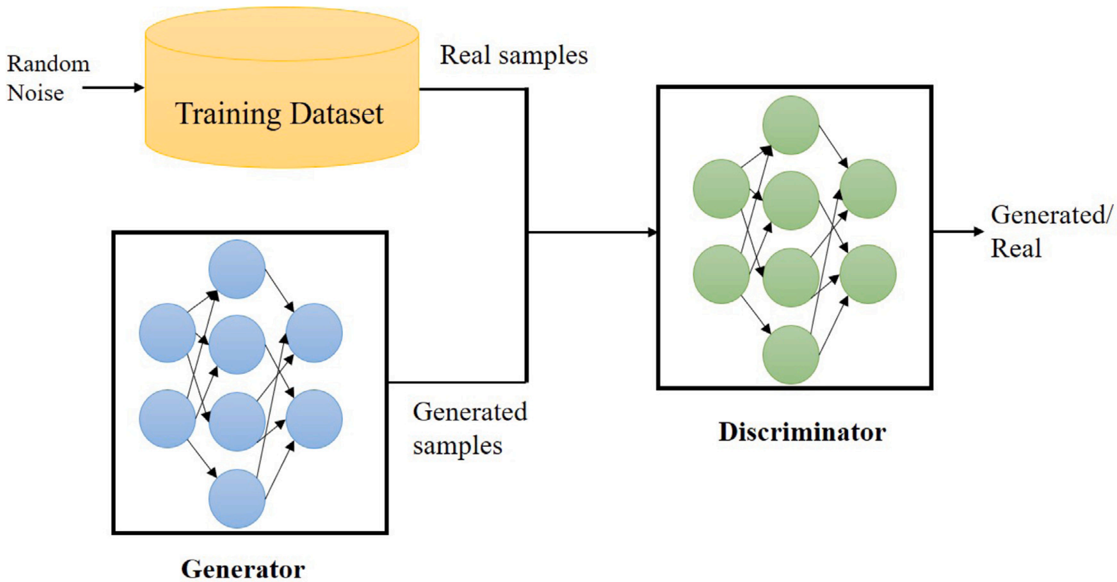

Fig. 13. Structural diagram of an Generative Adversarial Network (GAN).

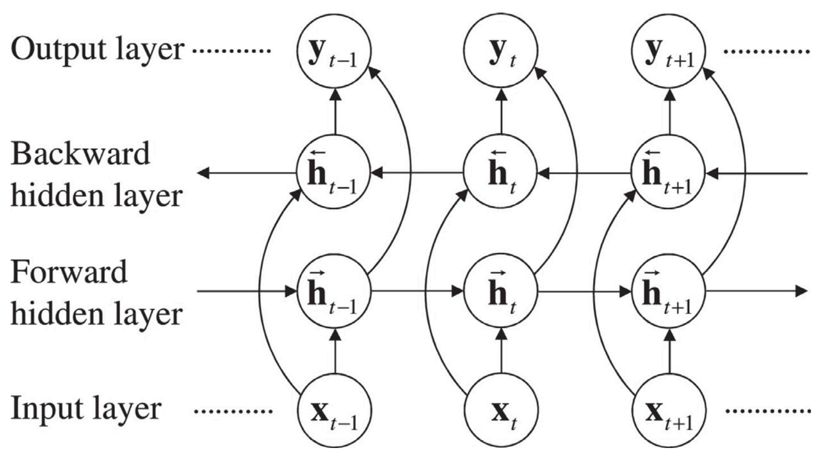

Fig. 14. Structural diagram of a bidirectional recurrent neural network (BRNN) (Ogawa and Hori, 2017).

$$y_t = s(w_{\overrightarrow{h},y}\overrightarrow{h}_t + w_{\overleftarrow{h},y}\overleftarrow{h}_t + b_y) \tag{36}$$

where x_t represents the input vector at time step t, $\overrightarrow{h}$ represents the activation vector on the forward hidden layer, $\overleftarrow{h}$ represents the activation vector on the backward hidden layer at time t, w represents the weight matrix and b represents the bias. $f(\cdot)$ represents the activation function of each node in hidden layer, $s(\cdot)$ denotes the softmax function and y_t is the probability of the output at time t.

Table 1
Simulation results of studied models on the MIDC dataset (Qing and Niu, 2018).

Algorithm	Testing RMSE
Persistence	209.2509
LR	230.9867
BPNN	133.5313
LSTM	76.245

4. Solar irradiance prediction using deep learning techniques

The accurate forecasting of solar irradiance for different forecasting horizons is one of the most desirable factors for the efficient functioning of solar energy systems. Therefore, this section presents an extensive review of various deep learning-based studies for solar irradiance forecasting for different forecasting horizons.

4.1. LSTM based solar irradiance forecasting model

LSTM models are trendy in solving time-series based forecasting problems. Thus, many studies have employed LSTMs to develop solar irradiance forecasting models in recent years.

Yu et al. (2019) applied the LSTM model to predict an hour ahead solar irradiance in three different locations of USA, including Atlanta, New York, and Hawaii. The developed model has considered clear sky index, relative humidity, cloud type, dew point, solar zenith angle, temperature, precipitable water, wind speed and wind direction as input parameters. They collected the solar data for a period of 2013 to 2017 from National Solar Radiation Data Base (NSRDB). They reported that the proposed LSTM model shows an RMSE in a range of 45.84 W/m^2 and 41.37 W/m^2 for the considered locations.

Qing and Niu (2018) used an LSTM model for next day's hourly solar irradiance prediction. The model uses month, hour of the day, day of the month, wind speed, temperature, visibility, relative humidity, dew point and weather type as input parameters. The model is trained and

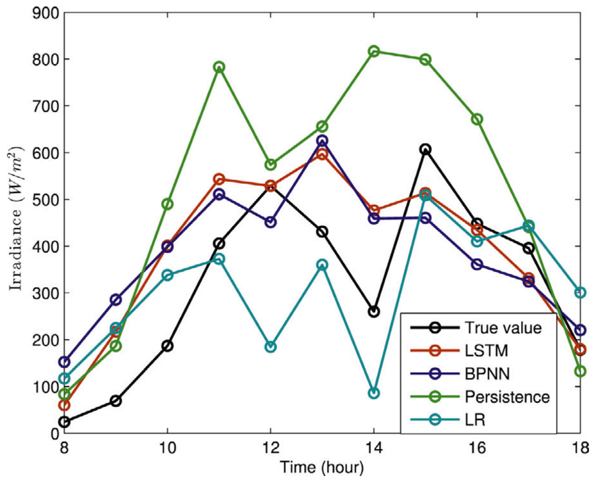

Fig. 15. A comparison of actual irradiance and predicted irradiance (Qing and Niu, 2018).

tested using 2.5 years data (March 2011 to August 2012 and January 2013 to December 2013) of a solar power plant located on the island of Santiago, Cape Verde. The developed model shows a good accuracy over other considered models, with an RMSE value of 76.245 W/m^2 (as shown in Table 1). The higher accuracy of the proposed LSTM model is also evident from Fig. 15, which shows an excellent agreement between actual and LSTM predicted solar irradiance.

Muhammad et al. (2019) used LSTM for hourly, daily and yearly solar irradiance prediction in Seoul, Korea. They retrieved the solar data from 2001 to 2017 from Korea Meteorological Administration (KMA) database. The model is trained using the historical data of solar irradiance to make future predictions.

Mishra and Palanisamy (2019) developed an LSTM to predict the solar irradiance for different forecasting horizons (i.e., intra-hour and intra-day). They validated the developed model with solar irradiance data of seven SURFRAD stations situated across the United States. They used numerous variables as input parameters, which includes downwelling global solar, upwelling global solar, photosynthetically active radiation, downwelling diffuse solar, downwelling thermal infrared, downwelling infrared dome temperature, upwelling thermal infrared, upwelling infrared dome temperature, downwelling infrared case temperature, direct-normal solar, global UVB, upwelling infrared case temperature, net solar, net infrared, net radiation, 10-meter air temperature, wind speed, station pressure, wind direction, relative humidity. Their proposed deep learning model has shown an improvement of 71.5% over traditional machine learning models.

Chandola et al. (2020) developed a deep LSTM network for multiple horizons (i.e., 3/6/24 h ahead) solar irradiance prediction in arid zones of India. The historical data of GHI, diffuse horizontal irradiance (DHI), direct normal irradiance (DNI), temperature, pressure, wind speed, relative humidity, dew point and wind direction is given as inputs to the LSTM network. The model is validated using five years dataset (2010 to 2014) of four different cities located in Thar desert, collected from NSRB. The developed model shows excellent performance with MAPE values ranging 6.79% to 10.47%.

Srivastava and Lessmann (2018) used an LSTM model forecast a day ahead solar irradiance using satellite data. The model is evaluated using the remote-sensing data of 21 locations, 16 of which are in mainland Europe and 5 in the US. Several atmospheric variables, including air pressure, cloud cover, maximum temperature, minimum temperature, specific humidity, etc., are used as input parameters. Obtained empirical results suggest that the developed LSTM performed better than other considered models. Moreover, LSTM has outperformed the persistence model with an average forecast skill value of 52.2%.

Jeon and Kim (2020) applied LSTM to predict the hourly solar irradiance for the next day. Several parameters are used as inputs such as the next-day weather forecast data of temperature, humidity, sky cover wind speed and precipitation. The weather forecast data is provided by the Korea Meteorological Administration. The data of several locations from the target region is used for the training of model. The predictive performance of the developed model was found to be substantial with an RMSE of 30 W/m^2.

Sorkun et al. (2017) applied LSTM and GRU for one hour ahead solar irradiance forecast. They employed a mono-variate approach, which uses historical time-series of solar irradiance to make predictions. Their developed LSTM and GRU models outperformed other traditional machine learning models in solar irradiance forecasting.

Alzahrani et al. (2017) applied a deep LSTM network, to forecast hourly solar radiation. They used the data of a Canadian solar farm to train and test the proposed model. The results obtained through the proposed approach are found to be superior to SVR and FFNN. Fig. 16 shows the prediction results of proposed model in different weather conditions, including few clouds, scattered clouds, overcast and clear-sky.

Obiora et al. (2020) forecasted the hourly solar irradiance forecast in Johannesburg city by using LSTM model. The LSTM network is trained using temperature, sunshine duration, relative humidity, and solar radiation as inputs. The dataset used to build the model is collected for a period of ten years, between 2009 and 2019 from National Oceanic and Atmospheric Administration's (NOAA). The prediction accuracy of the proposed model is compared with SVR and simulation results illustrate that the proposed LSTM network shows an improvement of 3.2% normalized root mean square error (nRMSE) over the SVR model.

Guariso et al. (2020) applied two types of neural networks, namely FFNN and LSTM, for multi-step horizon solar irradiance forecasting in Northern Italy. The proposed models employ different kinds of approaches such as Multi-Model (MM) and Multi-Output (MO) for the development of prediction model. The dataset used in their study is collected for a period of six years from 2014 to 2019, from a weather station in Como Campus, Italy. The model is trained with historical solar irradiance data. A comparative analysis of proposed model with a clear sky and two persistent models is also performed. The simulation results suggest that the developed models show an improvement in performance by incorporating the considered MM and MO approaches.

Kumari and Toshniwal (2019) applied an LSTM model for hourly solar irradiance forecasting. The developed model is validated for seven different climatic locations of India, namely Dehradun, Dharamshala, Gandhinagar, Guwahati, Jaipur, Pune and Thiruvananthapuram. The model is trained on five years dataset (2010–2014) provided by NSRDB. The historical GHI data and temperature, relative humidity, pressure, wind speed and dew point are feed as input to the model. The performance of the LSTM is compared with FFNN and XGBoost, and a significant improvement in the prediction accuracy of LSTM has been witnessed.

Chu et al. (2020) proposed a novel solar irradiance forecasting approach that utilizes image-based dataset and LSTM model. The proposed model is developed to forecast 5 to 60 min ahead solar irradiance. Two types of methods based on input variables given to the LSTM model are introduced. The first method considers solar irradiance 5 min before, current solar irradiance and center value as inputs. The second method considers solar irradiance 5 min earlier, latest solar irradiance, center value, variance value, red–blue comparison method and three step search method as input parameters. LSTM model trained according to second method has shown better prediction results.

Mukherjee et al. (2018) applied LSTM for hourly solar irradiance forecasting in Kharagpur, India using meteorological data and the historical irradiance data. They used the predicted solar irradiance for solar PV power output prediction at the same location. The model has considered the historical GHI trends, clear-sky DHI, clear-sky GHI,

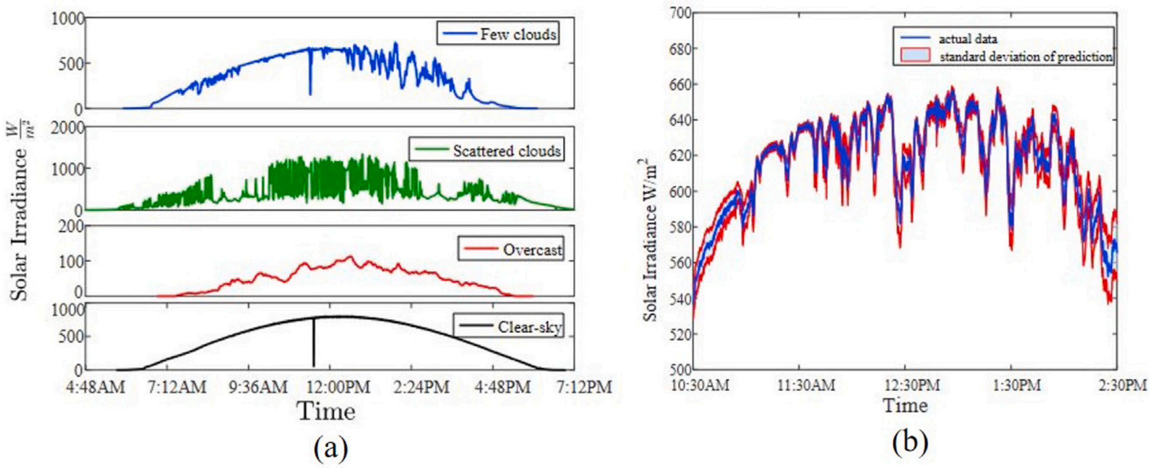

Fig. 16. (a) Solar irradiance forecasting in different weather conditions (b) solar forecasting for a day (Alzahrani et al., 2017).

clear-sky DNI, solar zenith angle, temperature, relative humidity, wind speed, hour, month and dew point as input parameters. Fifteen years of recorded data from 2000 to 2014 is employed to develop the forecasting models, which is provided by NSRDB. The proposed model has outperformed the ANN model with an RMSE value of 57.249 W/m^2.

Ashfaq et al. (2020) developed an LSTM network for an hour ahead GHI forecasting in Islamabad, Pakistan. The model is trained using historical GHI values and meteorological parameters such as ambient temperature, wind speed, the direction of wind, relative humidity, DHI, and DNI. The employed dataset is collected for a period of 55 months spanning from the year 2015–2020 from the meteorological station located in NUST Islamabad.

Justin et al. (2020) proposed a variant of LSTM, namely stacked LSTM integrated with principal component analysis (PCA) for solar irradiance forecasting. The data is collected for a period of six months (September 2019 to February 2020) from a weather station situated at Morong, Rizal. The employed dataset is consists of humidity, ambient temperature, station altitude, station temperature, sea level pressure, wind speed, illuminance and absolute pressure. A comparison between performance of the proposed stacked LSTM is performed with several other deep learning models, including CNN and Bidirectional-LSTM. The proposed model has shown comparatively accurate results with R^2 value 0.953 and MAE value 41.738 W/m^2.

de Araujo (2020) introduced a hybrid model which integrates Weather Research and Forecasting (WRF) model and Long Short Term Memory (LSTM) for solar irradiance prediction in Dili Timor Leste. The model is trained using one-year dataset recorded from January to December 2014 and used for testing for three months period from January to March 2015. The simulation results indicate that the developed model has shown good prediction results.

Kanagasundaram et al. (2019) applied a deep learning-based univariate LSTM model for performing short-term solar irradiance prediction. The data for model building is provided by a solar measuring station located in the Faculty of Engineering, University of Jaffna. The model is trained using two years of solar irradiance data recorded from 1st January 2014 to 1st January 2016 at 10-minute intervals. The performance of LSTM is compared with the ARIMA model, and the performance of the former model was found to be significantly better.

4.2. GRU based solar irradiance forecasting model

Wojtkiewicz et al. (2019) applied two types of Gated Recurrent Neural Networks: LSTM and Gated Recurrent Units (GRU) for an hour ahead solar irradiance prediction. They developed univariate forecasting models using historical time-series of solar irradiance data and a multivariate forecasting models using exogenous meteorological variables as input. The model is developed using a real-world dataset of an international airport in Phoenix, Arizona, recorded from the 1st of January 2004 to the 31st of December 2014, which NREL provides. According to the experimental results, the prediction accuracy of the multivariate LSTM and GRU is relatively higher as compared to their univariate counterparts.

Aslam et al. (2020) performed a comparative analysis of various state-of-the-art deep and machine learning algorithms, including GRU, LSTM, RNN, SVR and FFNN for solar irradiance forecasting. The model is trained on the historical irradiance and clear sky GHI data, downloaded from Korea Department of Meteorological Administration (KDMA) SURFRAD. The model is developed for two different locations, namely Seoul and Busan, in South Korea. The obtained simulation results illustrate that the employed deep learning models outperformed the considered machine learning models. Moreover, the prediction accuracy of GRU is slightly better than LSTM.

Yan et al. (2020) proposed a deep learning-based solar irradiance prediction model, which combines gated recurrent (GRU) and an attention mechanism to develop solar radiation prediction model. The model is trained to predict solar radiation according to four different seasons in Nevada desert in the US. The model is targeted to forecast for short-term forecasting horizons, including 5 min, 10 min, 20 min, and 30 min. The model is developed using the solar data of 2014 provided by the University of Nevada-Las Vegas and NREL. The historical solar irradiance, averaged and peak wind speed are given as inputs to the model.

Mukhoty et al. (2019) applied several deep models, including encoder–decoder networks of LSTM, bidirectional LSTM, RNN and GRU models to predict short-term solar irradiance. The model is trained using the fifteen-year (2000–2014) data of Kharagpur, India, provided by NREL. The solar irradiance and meteorological data are collected for a 10-kilo meter grid. A performance comparison between deep learning models with the existing machine learning models such as Gradient Boosted Regression Trees (GBRT) and Feed Forward Neural Networks (FFNN) is performed. The proposed model, namely encoder–decoder networks of LSTM has shown significant improvement over considered models.

4.3. Other deep learning-based solar irradiance forecasting model

Li et al. (2020a) developed a novel deep learning-based solar irradiance prediction model, namely multi-reservoir echo state network (MR-ESN). The proposed model take advantages of the deep architecture of echo state network (ESN). The model is developed for several forecasting horizons (i.e., 1 h and multi-hour ahead). Hourly solar

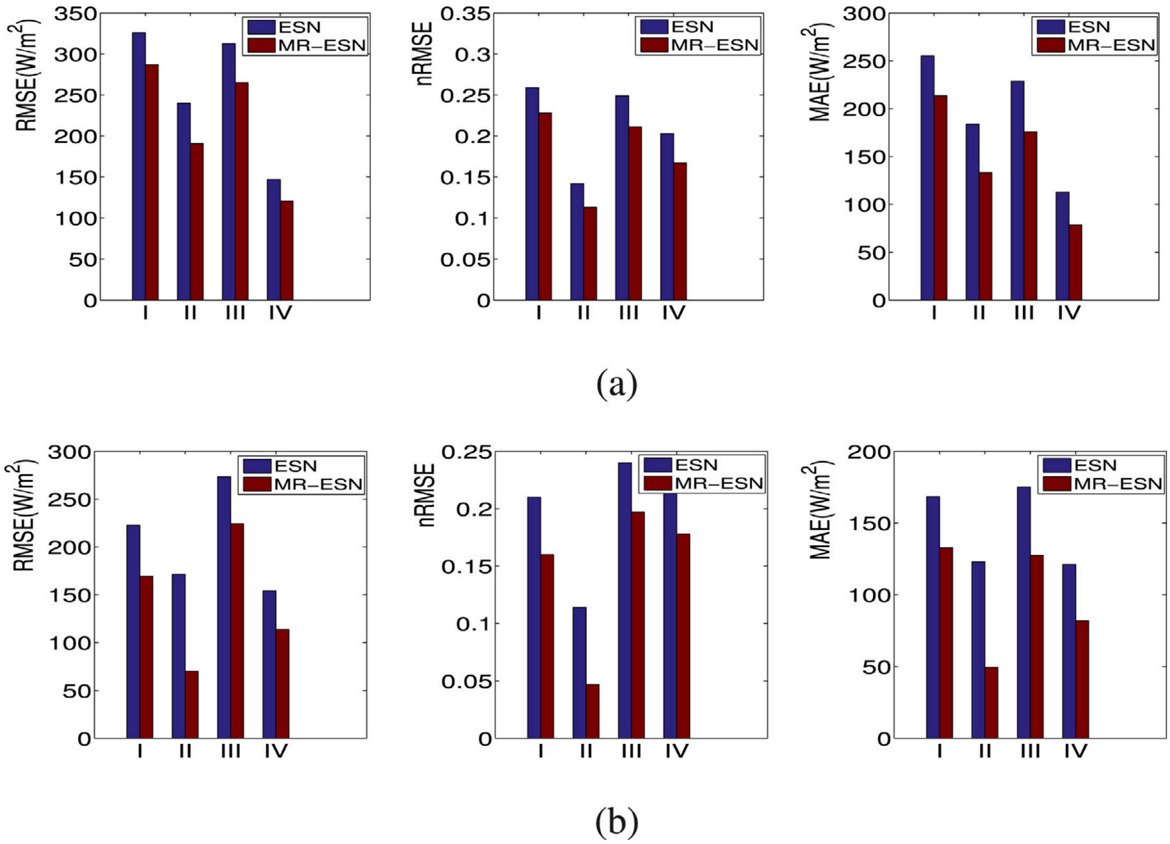

Fig. 17. 2-hour-ahead prediction comparison between ESN and MR-ESN for (a) Owens Lake South station; (b) Blythe NE station (Li et al., 2020a).

Table 2
RMSE and change ratio comparison between MR-ESN and ESN (Li et al., 2020a).

Prediction step	Evaluation period	RMSE (ESN)	RMSE (MR-ESN)	Reduction (%)
1-step	I	147.258	121.671	17.38
	II	132.787	63.014	52.55
	III	196.057	168.158	14.23
	IV	119.763	98.987	17.35
2-step	I	222.684	169.543	23.86
	II	171.536	70.068	59.15
	III	273.373	224.234	17.98
	IV	154.126	113.687	26.24
3-step	I	235.349	189.584	19.45
	II	156.275	72.064	53.89
	III	286.015	246.643	13.77
	IV	158.033	126.020	20.26

irradiance data of six different locations of California, including Davis, Seeley Owens Lake South, Blythe NE Markleeville and Salinas North, is collected from California Irrigation Management Information System. The quantitative simulation results demonstrate that the proposed MR-ESN model has a smaller prediction error than the considered basic model, namely, ESN, BP and Elman neural networks (ENNs). Moreover, the results obtained in Fig. 17 shows the prediction accuracy of MR-ESN in terms of RMSE, which is significantly higher than that of ESN. Also it is evident from the results demonstrated in Table 2 that with the increment in the forecasting horizon the prediction accuracy of models reduces.

Zhao et al. (2019) applied a 3D-CNN model for 10 min ahead direct normal irradiance prediction. The proposed model utilizes several consecutive ground-based cloud images to derive the spatial and temporal knowledge through cloud features. They used the GBC images and DNI data of 2 years (2013 to 2014) to develop the forecasting model collected from NREL. The proposed model has shown a forecast skills score of 17.06% over the persistence model.

Wang et al. (2019a) applied CNN and LSTM models to perform an end-to-end mapping to map the sky image to the solar irradiance data. The image dataset used in this study is real-time data captured by TSI-880, which is collected by NREL from July 1st, 2017 to June 30th, 2018. The analysis of simulation results suggests that the CNN model performed better as it shows better accuracy than LSTM mapping.

Pang et al. (2020) applied a deep recurrent neural network (RNN) with a moving window algorithm to predict short-term solar irradiance using the meteorological data measured at a weather station in Alabama. The prediction is performed for different sampling intervals including 1 h, 30 min and 10 min. They developed model with two parameters (i.e., outdoor dry-bulb temperature and time) as inputs for prediction. The model is trained using 7 days (May 22nd to May 28th, 2016) data while tested for a single day (May 29th, 2016). The proposed model's accuracy is compared with ANN and it was reported that RNN has higher prediction accuracy. The simulation results shown in Table 3 indicate that both ANN and RNN show acceptable accuracies,

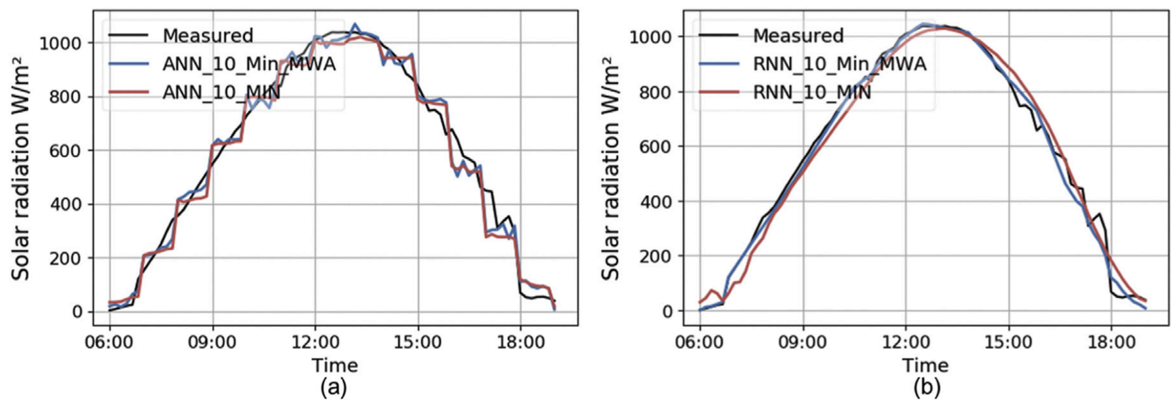

Fig. 18. The prediction results of (a) ANN and (b) RNN, with and without the incorporation of the moving window (Pang et al., 2020).

Table 3
Prediction accuracy of ANN and RNN models on a 10-min data sampling frequency (Pang et al., 2020).

	ANN	RNN	Improvement (%)
R^2	0.974	0.983	1%
RMSE	55.7	41.2	26%
CV(RMSE) (%)	9.41	7.64	19%
NMBE (%)	1.73	0.92	47%

with RNN slightly better than ANN. Fig. 18 shows the actual and predicted solar radiation at a 10-minute sampling frequency, representing that incorporating moving window mechanisms to the ANN and RNN helps in predicting solar radiation accurately.

Kaba et al. (2018) forecasted daily solar radiation using a deep neural network (DNN) in Turkey. The meteorological variables, including minimum temperature, cloud cover, sunshine duration and maximum temperature, and astronomical variable, extraterrestrial radiation, as input parameters. The model is trained and tested over a seven-year dataset collected from 34 stations, spanning the dates from 2001 to 2007. The proposed deep learning-based model has yielded very accurate prediction results, with a coefficient of determination of 0.98.

Sharda et al. (2020) proposed a novel Robust Self-Attention based Multi-horizon (RSAM) deep learning architecture to forecast solar irradiance. This model uses a self-attention-based transformer model for multi-variate solar irradiance forecasting. The model is trained using several meteorological and features, including temperature, cloud type, precipitable water, wind speed and direction, dew point, relative humidity, solar zenith angle, pressure), year, month, day, hour, along with residual features such as day residual, year residual, GHI residual and month residual, as input features. The model is validated on the dataset of two locations, namely Jammu and Kashmir (India) and Hotevilla (Arizona). The performance of the proposed model has been evaluated rigorously under different scenarios. The proposed RSAM model has shown an improvement of 58.89%, 18.60%, 6.42%, 3.94% and 13.22%, over Smart-Persistence, LSTM, CNN-LSTM, Attention-CNN-LSTM, and Attention-LSTM, respectively.

Mishra and Palanisamy (2018) proposed a unified architecture for multi-horizon short and long-term GHI forecasting using Recurrent Neural Networks (RNN). They used downwelling global solar, direct-normal solar, downwelling diffuse solar, upwelling global solar, global UVB, downwelling IR case temperature, downwelling IR dome temperature, downwelling thermal infrared, upwelling thermal infrared, relative humidity, net infrared, upwelling IR case temperature, upwelling IR dome temperature, photosynthetically active radiation, net solar, net radiation (netsolar+netir), 10-meter air temperature, wind speed, station pressure and wind direction, as input parameters. The model is build to forecast for different forecasting horizons (i.e., 1, 2, 3 and 4-hour ahead). The model is trained using seven SURFRAD observation site locations.

Zang et al. (2020a) developed a novel deep learning model, which combines deep belief network (DBN) and embedding clustering (EC) to estimate daily solar irradiance. The meteorological parameters, including daily mean wind speed, daily maximum dry-bulb temperature, daily mean relative humidity, daily minimum dry-bulb temperature, daily sunshine duration, daily mean dry-bulb temperature and daily global solar radiation are used as inputs of the model. The employed dataset is collected from 30 meteorological stations of different climatic locations in China. The model is trained using 22 years of data (1994 to 2015). The proposed hybrid model achieved the best prediction results in Beijing with an RMSE value of 0.282 MJ/m^2 and MAE value of 0.137 MJ/m^2, as shown in Table 4. Moreover, the probabilistic density error curves shown in Fig. 19 are evident to show the superiority of the proposed hybrid model (EC-DBN) over other considered models. The higher performance of proposed model at each meteorological station validate the global acceptance of DBN model for solar irradiance prediction.

Li et al. (2019c) proposed two deep learning-based multimodal solar irradiance forecasting models, named as hierarchical multimodal deep learning model (H-MDL) and wavelet decomposition multimodal deep learning model (SW-MDL). The proposed models are developed using a 12 years dataset provided by NREL. The employed dataset is consists of global horizontal irradiance, precipitation, wind speed, diffuse horizontal irradiance, zenith angle, direct normal irradiance, azimuth angle, temperature, turbidity, and hourly all-sky web cam images. The performance of the developed model is compared with basic prediction models such as ARIMA and ANN. The proposed model has achieved substantial performance gains over traditional machine learning models.

Lago et al. (2018) applied a deep neural network (DNN) to predict short-term solar irradiance in the Netherlands. The model is trained using the NWP forecasts, and the past irradiance values using satellite images, historical and forecasted values of the temperature and relative humidity, clear-sky irradiance for the next 6 h as input features. 30 locations in the Netherlands are selected, out of which, 5 locations are employed for the model training while remaining 25 locations are employed for evaluation of the model. A four-year dataset spanning from 1st January 2014 to 31st December 2017 is used for the training and validation of the proposed model. The proposed deep learning model has turned out to be an excellent replacement for basic models.

Madhiarasan and Deepa (2016) also applied a DNN model trained with self-regulated particle swarm optimization (SPSO) algorithm. The model is trained with several meteorological parameters such as minimum temperature, maximum temperature, sunshine hours, wind speed and direction, pressure, cloud cover, relative humidity, precipitation of water content, dew point, pressure and direct normal irradiance. The dataset employed to develop the model is collected from NOAA,

Table 4
The performance comparison of considered models at Beijing, Kunming, Changsha and Hefei stations (Zang et al., 2020a).

Model	Beijing		Kunming		Changsha		Hefei	
	MAE	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**
SVR	0.180	0.306	0.240	0.353	0.160	0.271	0.183	0.268
GPR	0.164	0.285	0.216	0.345	0.144	0.256	0.147	0.259
ANFIS	0.154	0.287	0.223	0.355	0.146	0.267	0.146	0.259
DBN	0.148	0.291	0.201	0.344	0.137	0.270	0.146	0.273
Functional DBN	0.147	0.289	0.199	**0.333**	0.132	0.263	0.145	0.266
EC + Functional DBN	**0.137**	**0.282**	**0.187**	0.340	**0.125**	**0.252**	**0.140**	**0.254**

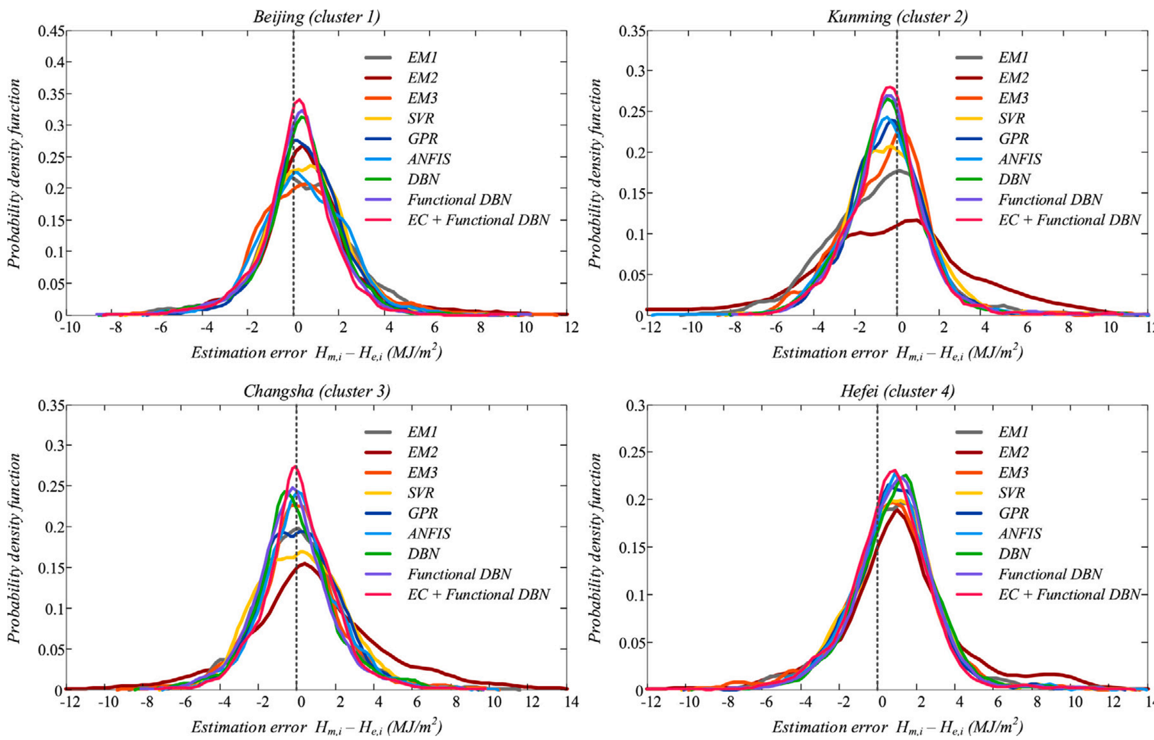

Fig. 19. Probabilistic density curves of hourly errors at Beijing, Kunming, Changsha and Hefei stations (Zang et al., 2020a).

United States. The developed model's accuracy is found to be relatively higher than several existing models, including MLP, SVM, ELM, and basic DNN.

Peng et al. (2021) proposed a deep learning-based solar irradiance forecasting framework that combines sine cosine algorithm (SCA), BiLSTM, and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN). The CEEMDAN is used to decompose the time-series data into certain periodic intrinsic mode functions (IMFs). Further, an autocorrelation function (ACF) and a partial autocorrelation function (PACF) are applied to identify the solar radiation patterns. Finally, the BiLSTM optimized using the SCA algorithm is applied for forecasting. The model is trained using the solar radiation data of a location near Dauphin Island, Alabama. The proposed CEN-SCA-BiLSTM model's performance is found to be better than other considered models, including ANN, KNNR, BiLSTM, SCA-BiLSTM, SVR, CEEMDAN-ANNCEN-ANN and CEN-BiLSTM. Additionally, the best performance is yielded in the autumn season, followed by the winter, summer and spring seasons (as shown in Fig. 20).

Brahma and Wadhvani (2020) proposed two different variants of LSTM, namely bidirectional long short-term memory (BiLSTM), attention LSTM and GRU for daily solar irradiance forecast for two Indian locations. The models are developed using 36 years (1983–2019) dataset provided by NASA's POWER project. They focused on developing the mono-variate solar irradiance forecasting model which considers the historical solar irradiance values as inputs to the models. Moreover, the historical solar irradiance data of neighbor locations of target locations are also given as inputs to the model. The developed models are used for multi-step ahead forecasting from 4 days to 10 days ahead. The obtained results suggest that the BiLSTM has shown higher accuracy as compared to other deep learning models.

Song and Brown (2019) applied two deep learning models, namely LSTM and temporal convolutional networks (TCN), for short-term solar irradiance forecasting. The solar irradiance data to train the model is collected from the University of Oregon from 2013 to 2016. The weather parameters, including wind speed, temperature, weather condition, dew point, and solar irradiance are given to the model as inputs. The obtained results suggest that the LSTM model shows high prediction accuracy while TCN model is preferable in terms of space and time complexity.

Li et al. (2020b) proposed a novel and advanced variant of RNN, namely chain-structure echo state network (CESN), for an hour ahead solar radiation forecasting. The proposed model analyses the spatio-temporal behavior of the data and it is computationally less expensive and has a fast learning speed compared to RNN. The proposed model is developed using the solar irradiance data of six different locations in California. The data is downloaded from California Irrigation Management Information System (CIMIS) for 2017. Experimental results suggest that the proposed CESN model shows higher performance than backpropagation (BP) ENNs and classical ESNs.

Andrianakos et al. (2019) used generative adversarial networks (GANs) for the sky image prediction. They developed a deep CNN model trained with adversarial in order to generate the realistic future

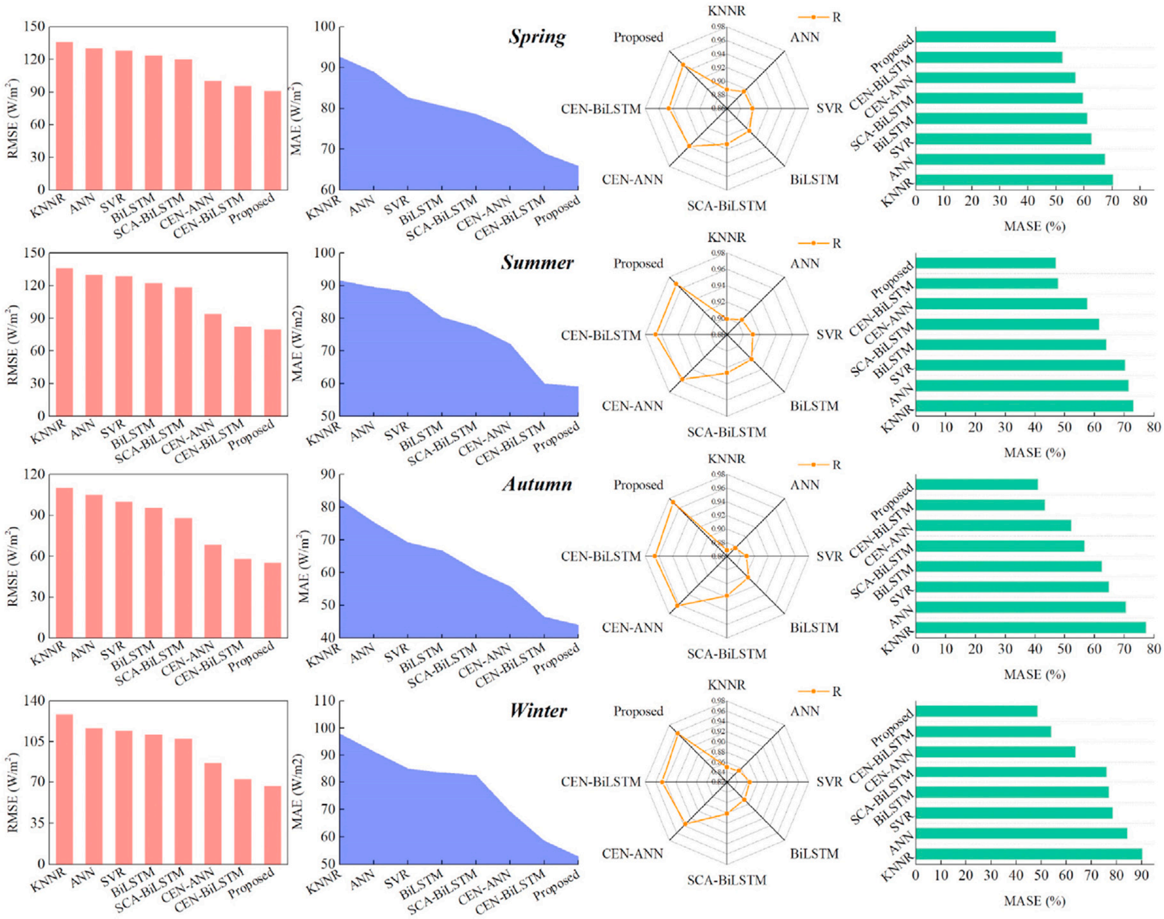

Fig. 20. Performance comparison of considered models in four different seasons (Peng et al., 2021).

images of cloud. The dataset employed in the study is an all-sky images dataset collected from physics department at the University of Patras. The considered dataset contains 1.5 million images obtained for a period of August 2014 to April 2017. The obtained results suggested that the images obtained by the model without including the adversarial loss are quite blurred.

Zhang et al. (2020) developed a novel solarGAN model which has the capability of multivariate solar data imputation. They used a basic GAN and a modified Wasserstein GAN (WGAN) named as solarGAN to provide an unsupervised framework for data imputation in solar time-series data. They employed a publicly available dataset from GEFCom 2014 solar track to conduct their study. The proposed model shows exemplary performance by reducing the error by 23.9% as compared to basic machine learning and GAN model.

4.4. Deep hybrid solar irradiance forecasting model

Li et al. (2020) proposed a novel Integrated-bidirectional long short-term memory (Integrated BiLSTM), which has two sub-models: the daily average irradiance prediction model and the irradiance amplitude prediction model for hourly solar irradiance prediction in United States. The employed dataset is obtained for 25 measurement stations from the National Water and Climate Center of the US. The meteorological variables, Wind direction, Maximum wind speed, Average wind speed, Vapor Pressure, Relative humidity, including Average temperature, Maximum temperature, Minimum temperature, Dew point temperature, Maximum relative humidity, Minimum relative humidity, etc. have been used as inputs to the model. The proposed model has shown higher prediction accuracy compared to several competitive prediction algorithms including SVR, LSTM, BiLSTM, etc.

Bendali et al. (2020) proposed a novel hybrid method, which uses genetic algorithm (GA) to optimize the deep neural network (GRU, LSTM and RNN) for solar irradiance forecasting. The model is developed using the time series data of solar irradiance recorded from 2016 to 2019 for the location of Fes, Moroccan city. The performance of the developed models is evaluated rigorously for different seasons, including summer, autumn, winter and spring. The incorporation of GA to the deep learning models has improved their performance significantly. LSTM-GA and GRU-GA have shown relatively better performance than RNN-GA.

Abdel-Nasser et al. (2020) proposed a hybrid model which combines LSTMs and Choquet integral based aggregation function to forecast solar irradiance for six different locations of Finland. The historical solar irradiance data is given as input to the model. The employed dataset is collected from the Finnish meteorological institute. The proposed model shows the RMSE in a range of 26 to 30 W/m^2, reflecting a good prediction performance.

Zang et al. (2020b) developed a hybrid of CNN and LSTM to predict an hour ahead solar irradiance. The model is targeted to extract the spatial and temporal features from the meteorological data of 34 locations in Texas. Dew point temperature, solar zenith angle, wind speed, precipitable water, relative humidity, wind direction and temperature are employed as input features to predict the global horizontal irradiance. Model is trained using seven years (2006 to 2012) data collected from National Solar Radiation Data Base. The proposed CNN-LSTM predicted solar irradiance had shown a good agreement with actual solar irradiance with a correlation coefficient of 0.9753.

Prado-Rujas et al. (2021) proposed a deep hybrid model which combines CNN and LSTM to develop an hour ahead solar irradiance and clear sky index forecasting framework. The proposed framework is

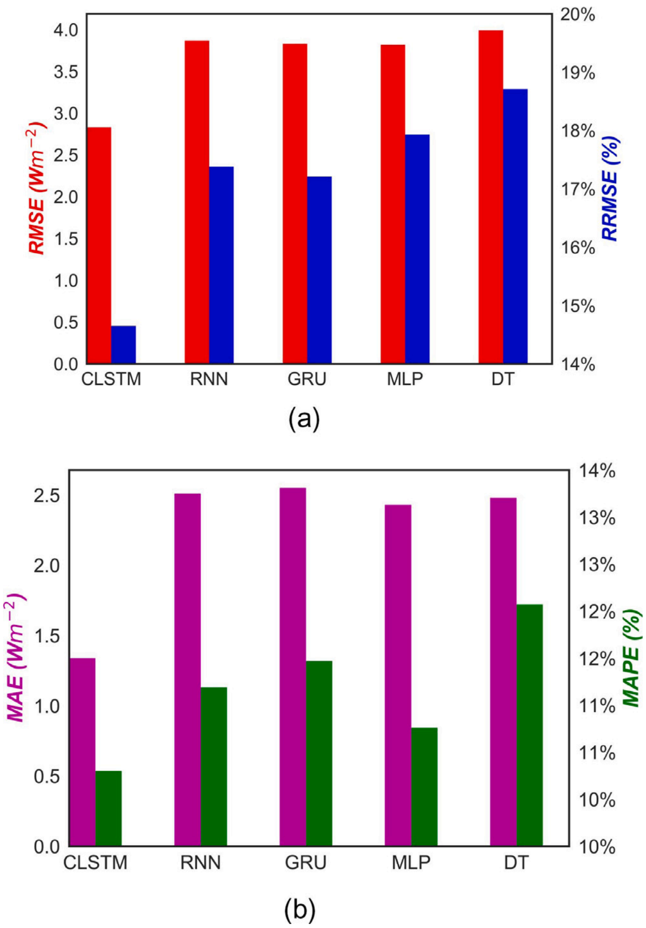

Fig. 21. Performance of CLSTM hybrid model for 1-day GSR prediction (Ghimire et al., 2019).

designed to use the historical solar irradiance data as input and does not use any exogenous variables. The model is trained using Oahu's solar dataset downloaded from the National Renewable Energy Laboratory (NREL). Twenty months (March 2010 to October 2011) of measured data is employed to train and test the model. The developed model has shown a significant improvement over considered baseline models, which is evident from the obtained forecast skill score ranging from 7.4% to 41%.

Ziyabari et al. (2020) developed an end-to-end novel hybrid deep architecture that integrates residual network (ResNet) and LSTM for short-time solar irradiance forecasting. The model is validated using solar data of 12 cities in Philadelphia, Pennsylvania. They utilized the eight-year dataset (2000 and 2017) for model development, collected from the NSRDB. The meteorological variables, including global horizontal irradiance, clear-sky GHI, diffuse horizon irradiance, clear-sky DHI, direct normal irradiance, clear-sky DNI, dew point, wind speed, temperature, precipitable water, cloud type wind direction, solar zenith angle, relative humidity and pressure are used as input features. Their proposed ResNet-LSTM hybrid model reduces the prediction error by 52.44% and 17.07% compared to basic LSTM and ResNet, respectively.

Ghimire et al. (2019) proposed a hybrid deep learning model (CLSTM) combining CNN and LSTM models for half-hourly solar radiation forecasting in Alice Spring, Australia. The model is developed for short and longer-term forecast horizons. The developed model is assessed for daily, weekly, and n-Month solar irradiance forecasting horizons (n=1, 2, 3, 4, 5, 6, 7, 8). The 12 years 8 months data (01 January 2006 to 31 August 2018) is used for model development. The historical solar irradiance data is used as input features. The proposed CLSTM model has shown better performance than benchmarked single deep learning and machine learning models. The proposed model has outperformed the considered models in terms of each considered evaluation metrics, namely RMSE, RRMSE, MAE and MAPE, as shown in Fig. 21. Moreover, Table 5 shows promoting percentages to demonstrate the improvement in the model's performance.

Wang et al. (2018e) proposed an advanced hybrid deep learning model based on wavelet decomposition, CNN and LSTM for day-ahead solar irradiance forecasting in North Carolina. The input to the model is the historical time series solar irradiance data, which is decomposed into four weather types. The model is validated for two locations, including Elizabeth City State University and Desert Rock Station, whose data is collected from NREL and National Oceanic & Atmospheric Administration(NOAA) Earth System Research Laboratory, respectively.

Husein and Chung (2019) proposed a hybrid of LSTM and recurrent neural network (RNN), named as LSTM-RNN model for day-ahead solar irradiance forecasting. The model is validated on the data of several climatic locations, including the USA, Switzerland, Germany, and South Korea. The proposed model uses weather data, such as temperature, dew-point dry-bulb temperature, and relative humidity, as the input parameter. The sources of the employed dataset are as follows: Max Planck Institute of Biochemistry in Jena, Germany, Weather Station in Basel, Switzerland, Solar Radiation Research Laboratory (SRRL) in Golden, Colorado, USA, Korea Meteorological Administration(KMA) Weather Stations in Jeju, Busan, and Incheon. The authors reported that the proposed hybrid model achieved a forecast skill of 50.90% and up to 68.89% when compared to the persistence model.

Huang et al. (2020) proposed a novel hybrid model that combines LSTM and MLP network. The proposed model works on two-branch input (including primary input and auxiliary input) for an hour-ahead solar irradiance prediction. The primary input is consists of time-series of historical solar radiation, and auxiliary input is consists of meteorological variables at t and t-1 time instances. The data employed in their study is collected from a solar power plant in Denver, Colorado, USA. The model is trained and tested using a five years dataset. The developed model outperformed several machine learning models, including SVM, BPNN, random forest, RNN, and LSTM, by an improvement of 19.31%, 19.19%, 11.68%, 20.15% and 13.48%.

He et al. (2020) proposed a hybrid probabilistic prediction model, which combines a recurrent neural network and residual modeling. An LSTM-based point prediction is used for deterministic forecasts. Further, the deterministic forecast data is used to calculate the residual distributions. The variables, including the day of the month relative humidity, dew point temperature, cloud cover, east sea-level pressure, wind speed, the month of the year and the hour of the day, are used as inputs of the model. The model is developed using a ten years dataset downloaded from the official website of the MIDC. The proposed model has shown a superior prediction accuracy over ELM, RF, SVR, and LSTM.

Wang et al. (2019c) proposed a hybrid framework (SOM-LSTM) for very short-term solar irradiance prediction. The proposed framework utilizes self-organizing mapping (SOM) to cluster and labels the solar irradiance data. Next, a deep learning model, namely LSTM, is used to develop a forecasting models corresponding to each predicted label. The solar irradiance data is collected from Sioux Falls, South Dakota, USA. To show the superiority of proposed model, it is compared with several competitive models, including LSTM, back propagation (BP) neural network and SOM-BP and the performance of the proposed model is found to be better than other three.

Brahma et al. (2020) applied six variants of RNN techniques, namely RNN, Content-based Attention, GRU, Luong Attention, Self-Attention based RNN and LSTM for solar irradiance prediction. The performance of the developed models is compared using a thirty-seven year's dataset of two different locations. The developed models are trained using the historical time series data of solar irradiance without using any

Table 5
Promoting Percentages to represent the improvement of CLSTM model at multi-step forecast horizons in terms of RMSE, MAE and MAPE (Ghimire et al., 2019).

CLSTM vs. Competing Model Below	$\lambda MAPE$ (%)		λMAE (%)		$\lambda RMSE$ (%)	
	1D	1W	1D	1W	1D	1W
CNN	3.62	11.78	11.42	9.51	18.04	4.85
LSTM	25.29	23.23	63.65	13.05	61.11	15.19
GRU	34.66	19.14	41.11	37.38	42.69	25.40
RNN	37.37	8.05	63.39	13.90	59.42	11.60
DNN	26.20	44.17	50.41	50.82	49.35	38.36
MLP	18.94	36.72	38.63	59.70	36.66	52.10
DT	22.40	29.39	58.21	34.76	58.56	21.99

exogenous parameters. Prediction is made for different forecasting horizons. The obtained results suggest that the attention mechanism provides a remarkable improvement to the memory-based RNNs.

Jaihuni et al. (2020) proposed a partially amended hybrid model (PAHM), which combines bi-directional gated recurrent unit (Bi-GRU) and autoregressive integrated moving average (ARIMA) model for 5-min and 60-min ahead solar irradiance forecasting. The time-series data of several meteorological variables such as solar irradiance, relative humidity, wind direction temperature, sun hours and wind speed is considered as input. A dataset of 32 months collected from a weather station located in the Gyeongsang National University, JinjuCity, Republic of South Korea is used for model development. The proposed PAHM approach has improved the performance of simple hybrid of ARIMA and Bi-GRU by 5%.

Kumari and Toshniwal (2021a) introduced an ensemble model (XGBF-DNN) for hourly solar irradiance forecast, by integrating extreme gradient boosting forest and deep neural networks . The proposed model is validated for three locations of India, namely Delhi, Jaipur and Gangtok. The model is trained using temperature, pressure, wind speed, relative humidity, wind direction, hour of the day, clear sky index and month number, as inputs of the model. The performance of developed model is compared with the existing benchmarks, including smart persistence, RF, SVR, XGBoost, and DNN. The performance of proposed ensemble model is superior to other considered models at each location in each considered season, including winter, summer, monsoon and autumn (Kumari and Toshniwal, 2021a) (see Fig. 22).

Yeom et al. (2020) applied a hybrid of CNN and LSTM network, namely ConvLSTM, to predict hourly solar irradiance in the Korean Peninsula. The data is collected with the help of a COMS-MI satellite. The employed dataset contains 1100 sequential images, which are collected between 1 April 2011 and 31 December 2015. The obtained simulation results illustrate that the proposed ConvLSTM model has shown the highest prediction accuracy over RF and ANN, with an RMSE value of 71.334 W/m^2 and R^2 value of 0.895.

Wang et al. (2018b) developed a novel deep hybrid model which integrates the LSTM with least absolute shrinkage and selection operator (LASSO) to predict accurate short-term solar intensity. The proposed framework firstly clusters the data with the help of k-means++. Further, a prediction model is developed corresponding to each cluster. The proposed model uses LSTM to capture non linear features and LASSO, to capture the linear features in the data. The model is developed for two different datasets: Amherst, MA, USA (Feb 2006 to Jan 2013) and Harnhill and Diddington, UK (Aug 2011 to Dec 2012). The proposed approach has shown highly accurate forecasting results and outperformed all the baseline models.

Hong et al. (2020) introduced a novel day ahead solar irradiation forecasting model, which encodes the time-series data into images using the Gramian Angular Field and the Convolutional LSTM (ConvLSTM) network. The proposed model overcomes the drawback of LSTM model by eradicating the concept of one-dimensional forecasting. The model is developed using the satellite-derived GHI data collected from the SolarGIS database in Fuhai, Taiwan. The prediction accuracy of the proposed method is significantly better than the considered benchmark models, including ARIMA and LSTM.

Liu et al. (2019) proposed an ensemble spatio-temporal prediction model, named as variational Bayesian convolutional GRU (CovnGRU-VB) for solar irradiation forecasting. The proposed model efficiently handles the high dimension of temporal and spatial meteorological information through the use of a convolution operator in input-to-state and state-to-state transitions in the GRU. The model is trained using several meteorological variables such as global horizontal irradiation, precipitable water, solar zenith angle, wind direction, temperature, dew point, relative humidity, and wind speed. The studied area covers a spatial region bounded by longitudes $W97°$ and $W107°$ and latitudes $N33°$ and $N43°$, which consists of 400 sites and demonstrated by a 20×20 grid. The model is trained and tested on a two years dataset spanning from 1st January 2013 to 31st December 2014. The proposed ensemble model shows highly accurate prediction results as compared to several deep learning models, including RNN, DNN, GRU and LSTM.

Siddiqui et al. (2019) proposed a novel deep solar irradiance forecasting model which consists of two stages. Initially, a CNN model is used to encode a frame from a sky-video to retrieve a full-sky view. Next, a two-tier LSTM model observes the full-sky view for the future forecast. The proposed model is trained using a publicly available dataset of two different locations in the United States, namely Golden, Colorado and Tuscan, Arizona. The proposed model is developed to forecast for multiple time horizons, such as 1–4 h ahead of time.

5. Performance comparison and discussion

This section compares and discusses the accuracy of different deep learning based solar irradiance prediction models. Among several deep learning techniques, LSTM is extensively applied in solar irradiance forecasting. For instance, Srivastava and Lessmann (2018) also developed an LSTM model to forecast a day ahead solar irradiance using remote-sensing data of 21 locations if Europe and US. Their proposed model showed an improvement of 52.2% over smart persistence model. Similarly, Yu et al. (2019) applied LSTM to predict an hour ahead solar irradiance for three different sites in USA. The developed model showed the lowest RMSE of 41.37 W/m^2. LSTM models have shown high prediction accuracy in solar irradiance forecasting. However, their performance is further improved by incorporating different mechanism to it and introducing its variants. For instance, Brahma and Wadhvani (2020) introduced two different variants of LSTM, namely BiLSTM and attention-based LSTM for daily solar irradiance forecast for two Indian locations. The gating mechanism and memory cells incorporated in the LSTM architecture make them efficient in learning long-term dependencies in data. Therefore, LSTM and its other variants are highly capable of processing solar irradiance time-series data and show high prediction accuracy. Further, few researchers applied GRUs for solar irradiance prediction (Wojtkiewicz et al., 2019). In GRUs, the forget and input gates are merged together, which enhances the design complexity. GRUs are less computationally expensive as they train less parameters and use less memory and hence, execute faster. On the other hand, LSTMs are comparatively more expensive but highly accurate at the same time.

Later, Zhao et al. (2019) introduced a CNN model to predict 10 min ahead direct normal irradiance. The proposed model utilized several

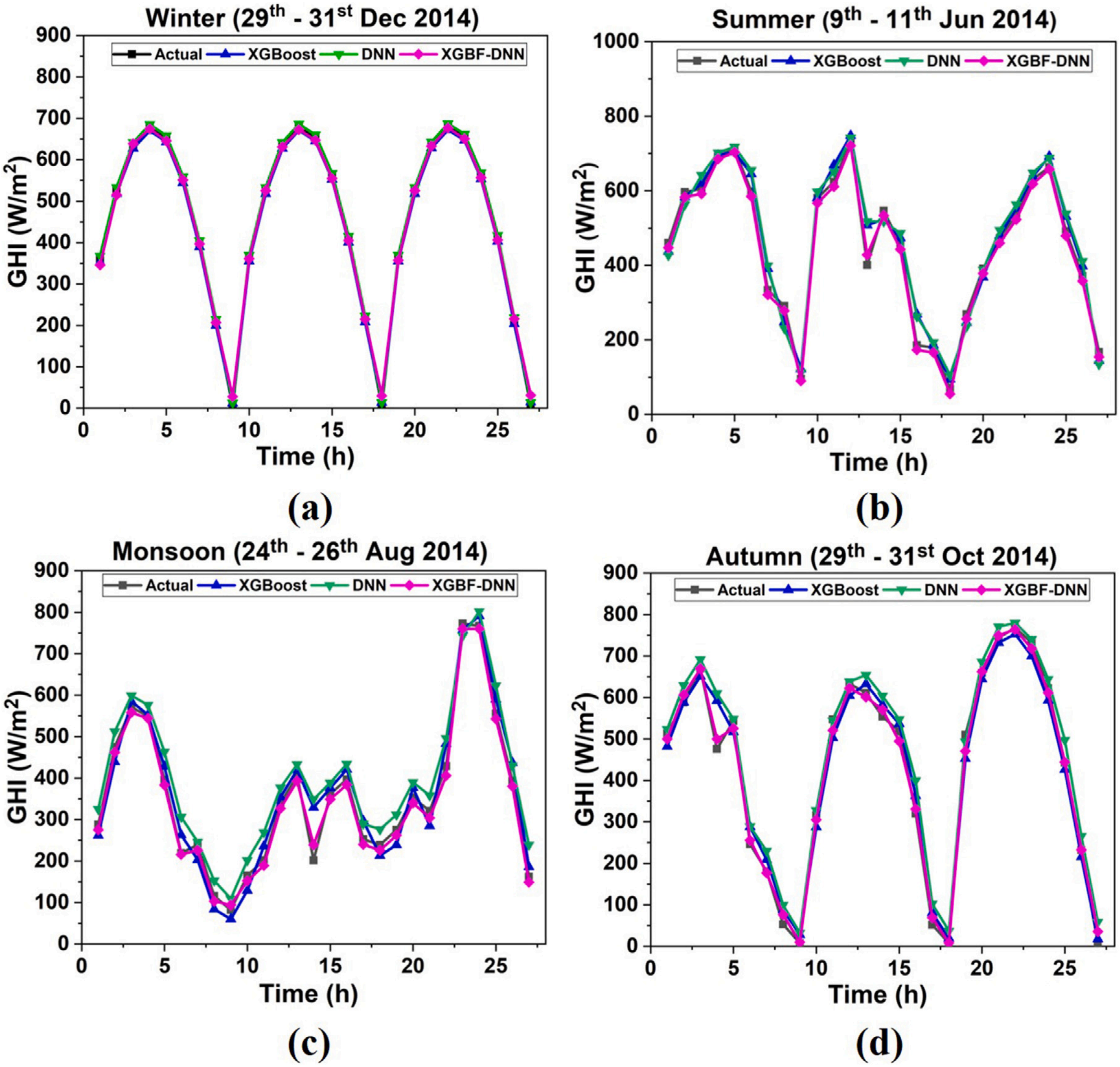

Fig. 22. Actual and forecasted GHI in Gangtok under different seasons. (a) Winter, (b) Summer, (c) Monsoon and (d) Autumn (Kumari and Toshniwal, 2021a).

consecutive ground-based cloud images to derive the spatial and temporal features and showed an improvement of 17.06% over persistence model. The architecture of CNN contains convolutional and pooling layers, which efficiently extracts features from the images. Therefore, CNN works well for the case when solar irradiance data either has image data or can be converted to the 2-dimensional data. Another deep learning model which gained popularity in solar irradiance forecasting is DBN (Zang et al., 2020a). The inherent basic structure in the DBN is a restricted Boltzmann machine. The network parameters are initialized using layer-by-layer unsupervised training method. Therefore, the DBN can be used for renewable energy predictions when typical features in the input data are not explicitly detectable.

Furthermore, many researchers applied RNN for solar irradiance forecasting. For instance, Mishra and Palanisamy (2018) proposed a multi-horizon GHI forecasting model using RNN, which showed an average RMSE of 18.57 W/m^2 over different forecasting horizons. The primary characteristic of RNN is that it has both internal feedback as well as feedforward connections between the neurons. These connections provide a memory function to the RNNs, which make RNN suitable for processing time-series solar data. To further enhance the prediction accuracies of deep learning models, different type of hybrid models comprised of deep learning models are also proposed in literature. For instance, Zang et al. (2020b) developed a hybrid of model CNN and LSTM, Husein and Chung (2019) proposed a hybrid model using LSTM and RNN, Bendali et al. (2020) proposed a novel hybrid method, which uses GA to optimize the deep neural network (GRU, LSTM and RNN) for solar irradiance forecasting. The obtained results suggest that assembling multiple models together enhance their predictive performance. The deep hybrid models combine several deep learning models to exploit the advantages of multiple models to attain higher performance. The advantages, disadvantages and applicability of above mentioned methods is given in Table 6.

6. Conclusion

In this work, a comprehensive review of solar irradiance forecasting models based on a popular emerging approach, namely deep learning, is presented. There are a lot of deep learning-based solar irradiance forecasting models available in literature. The deep architecture of these models helps in extracting the high-level and non-linear complex features from the solar data. This paper provides a detailed description of several popular deep learning models, including long short-term memory, deep belief network, convolutional neural network, recurrent neural network, gated recurrent unit, and echo state network, along with their working mechanism, advantages and limitations from the perspective of solar irradiance forecasting. Moreover, a brief discussion

Table 6
The benefits, drawbacks and applicability scenarios of different deep learning models for solar irradiance prediction.

Model	Advantage	Disadvantage	Scenarios
LSTM	Capable of handling long-term dependencies in time-series data	Computationally expensive	The solar data has time-series data
GRU	Less complex design; less memory; faster execution; less computationally expensive	Slow convergence and low learning efficiency	The computation resources are limited
CNN	Capable of handling image dataset; capable of spatial feature extraction	Computationally expensive; features should be predetermined	The solar data set contains images or can be converted to 2-dimensional data
DBN	Capable of extracting unsupervised feature; less computationally expensive	Unable to process multi-dimensional meteorological data	Not considering multiple variables
RNN	Capable to process time-series data; computationally efficient	Unable to determine features effectively	The solar data has time-series data
Hybrid	Capable of extracting different types of features from the data; high accuracy	Computationally expensive	The solar data contains different characteristics such as spatial and temporal information

about the factors, which influence the preciseness and accuracy of forecasting models, such as forecasting horizons, weather classifications, and evaluation metrics, is also provided. Finally, a brief description of the existing studies that utilized deep learning models for solar irradiance forecasting along with input parameters, data sources and achieved performances has been given. Additionally, the present study demonstrates several existing simulation results, which validate the effectiveness and excellence of deep learning-based solar irradiance forecasting models over traditional machine learning methods. The RMSE of LSTM varies in a range of 30 W/m^2 to 76 W/m^2 depending on the forecasting horizon. Moreover, the prediction accuracy is further improved by utilizing the hybrid of deep learning models. For instance, the hybrid of CNN-LSTM has shown the improvement of 3.62%, 25.29%, 34.66%, 37.37% and 26.20% over CNN, LSTM, GRU, RNN and DNN, respectively. Several important conclusions are drawn from this review which are as follows:

- The forecasting horizon plays very important role in the preciseness of the prediction results of a model. As the forecasting horizon increases the performance of a solar irradiance forecasting model usually decreases. Therefore, prediction models should be selected in accordance with the forecasting horizon.
- The performance of a forecasting model varies with the change in weather. For instance, few forecasting models incur less accuracy in unstable sky conditions while other might show comparatively better performance. Therefore, weather classification is one of the most influential factors in enhancing the predictive performance of solar irradiance forecasting models, necessitating the inclusion of weather types during forecasting.
- There are a lot of deep learning models for solar irradiance forecasting. Some are used more often (LSTM, RNN, DNN) while others are rarely used (DBN, ESN, CNN). Few of them are computationally expensive while highly accurate at the same time. Few are computationally less expensive but have slow convergence and low learning efficiency. Conclusively, the deep learning techniques are still at an infant stage and their potential should be explored more to solve complex time-series forecasting problems.
- Single deep learning models have several limitations. The findings of the present review suggest that hybrid models which involve the combination of different models enhance the accuracy and can be recommended over basic deep learning models.
- The most recent information and comparative analysis of deep learning models presented in this work can enrich the future of researchers, planners and forecasting professionals from solar energy systems to select the deep learning model that can assist them in enhancing the performance of forecasting models.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The first author is grateful to Ministry of Education, Government of India for the doctoral fellowship. The authors would like to express their gratitude towards Director, IITR for providing the research facilities.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.128566.

References

Abdel-Nasser, M., Mahmoud, K., Lehtonen, M., 2020. Reliable solar irradiance forecasting approach based on Choquet integral and deep LSTMs. IEEE Trans. Ind. Inf. 17 (3), 1873–1881.

Aguiar, L.M., Pereira, B., Lauret, P., Díaz, F., David, M., 2016. Combining solar irradiance measurements, satellite-derived data and a numerical weather prediction model to improve intra-day solar forecasting. Renew. Energy 97, 599–610.

Ahmad, M.W., Mourshed, M., Rezgui, Y., 2018. Tree-based ensemble methods for predicting PV power generation and their comparison with support vector regression. Energy 164, 465–474.

Akarslan, E., Hocaoglu, F.O., Edizkan, R., 2018. Novel short term solar irradiance forecasting models. Renew. Energy 123, 58–66.

Alfadda, A., Rahman, S., Pipattanasomporn, M., 2018. Solar irradiance forecast using aerosols measurements: A data driven approach. Sol. Energy 170, 924–939.

Alsina, E.F., Bortolini, M., Gamberi, M., Regattieri, A., 2016. Artificial neural network optimisation for monthly average daily global solar radiation prediction. Energy Convers. Manage. 120, 320–329.

Alzahrani, A., Shamsi, P., Dagli, C., Ferdowsi, M., 2017. Solar irradiance forecasting using deep neural networks. Procedia Comput. Sci. 114, 304–313.

Anderson, D., Leach, M., 2004. Harvesting and redistributing renewable energy: on the role of gas and electricity grids to overcome intermittency through the generation and storage of hydrogen. Energy Policy 32 (14), 1603–1614.

Andrianakos, G., Tsourounis, D., Oikonomou, S., Kastaniotis, D., Economou, G., Kazantzidis, A., 2019. Sky image forecasting with generative adversarial networks for cloud coverage prediction. In: 2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA). IEEE, pp. 1–7.

Angstrom, A., 1924. Solar and terrestrial radiation. Report to the international commission for solar research on actinometric investigations of solar and atmospheric radiation. Q. J. R. Meteorol. Soc. 50 (210), 121–126.

Antonanzas-Torres, F., Urraca, R., Polo, J., Perpiñán Lamigueiro, O., Escobar, R., 2019. Clear sky solar irradiance models: A review of seventy models. Renew. Sustain. Energy Rev. 107, 374–387.

APRICUM, 2016. Global distribution of PV demand, https://www.apricum-group.com/installing-60-global-pv-capacity-2016-whats-store-giant-chinese-u-s-pv-markets/.

Ashfaq, Q., Ulasyar, A., Zad, H.S., Khattak, A., Imran, K., 2020. Hour-ahead global horizontal irradiance forecasting using long short term memory network. In: 2020 IEEE 23rd International Multitopic Conference (INMIC). IEEE, pp. 1–6.

Aslam, M., Lee, J.-M., Kim, H.-S., Lee, S.-J., Hong, S., 2020. Deep learning models for long-term solar radiation forecasting considering microgrid installation: A comparative study. Energies 13 (1), 147.

Badescu, V., Gueymard, C.A., Cheval, S., Oprea, C., Baciu, M., Dumitrescu, A., Iacobescu, F., Milos, I., Rada, C., 2013. Accuracy analysis for fifty-four clear-sky solar radiation models using routine hourly global irradiance measurements in Romania. Renew. Energy 55, 85–103.

Bae, K.Y., Jang, H.S., Sung, D.K., 2016. Hourly solar irradiance prediction based on support vector machine and its error analysis. IEEE Trans. Power Syst. 32 (2), 935–945.

Bahdanau, D., Cho, K., Bengio, Y., 2014. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.

Bandara, K., Bergmeir, C., Smyl, S., 2017. Forecasting across time series databases using long short-term memory networks on groups of similar series. arXiv preprint arXiv:1710.03222, 8, 805–815.

Bendali, W., Saber, I., Bourachdi, B., Boussetta, M., Mourad, Y., 2020. Deep learning using genetic algorithm optimization for short term solar irradiance forecasting. In: 2020 Fourth International Conference on Intelligent Computing in Data Sciences (ICDS). IEEE, pp. 1–8.

Bengio, Y., 2009. Learning Deep Architectures for AI. Now Publishers Inc.

Brahma, B., Wadhvani, R., 2020. Solar irradiance forecasting based on deep learning methodologies and multi-site data. Symmetry 12 (11), 1830.

Brahma, B., Wadhvani, R., Shukla, S., 2020. Attention mechanism for developing wind speed and solar irradiance forecasting models. Wind Eng. 0309524X20981885.

Breiman, L., et al., 1996. Heuristics of instability and stabilization in model selection. Ann. Statist. 24 (6), 2350–2383.

Bristow, K.L., Campbell, G.S., 1984. On the relationship between incoming solar radiation and daily maximum and minimum temperature. Agricult. Forest Meteorol. 31 (2), 159–166.

Chandola, D., Gupta, H., Tikkiwal, V.A., Bohra, M.K., 2020. Multi-step ahead forecasting of global solar radiation for arid zones using deep learning. Procedia Comput. Sci. 167, 626–635.

Chen, J.-L., He, L., Yang, H., Ma, M., Chen, Q., Wu, S.-J., Xiao, Z.-l., 2019a. Empirical models for estimating monthly global solar radiation: A most comprehensive review and comparative case study in China. Renew. Sustain. Energy Rev. 108, 91–111.

Chen, J., Jing, H., Chang, Y., Liu, Q., 2019b. Gated recurrent unit based recurrent neural network for remaining useful life prediction of nonlinear deterioration process. Reliab. Eng. Syst. Saf. 185, 372–382.

Chen, Y., Zhang, S., Zhang, W., Peng, J., Cai, Y., 2019c. Multifactor spatio-temporal correlation model based on a combination of convolutional neural network and long short-term memory neural network for wind speed forecasting. Energy Convers. Manage. 185, 783–799.

Chen, Y., Zhao, X., Jia, X., 2015. Spectral–spatial classification of hyperspectral data based on deep belief network. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 8 (6), 2381–2392.

Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., Bengio, Y., 2014. Learning phrase representations using RNN encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078.

Choi, H., Cho, K., Bengio, Y., 2018. Fine-grained attention mechanism for neural machine translation. Neurocomputing 284, 171–176.

Chow, C.W., Urquhart, B., Lave, M., Dominguez, A., Kleissl, J., Shields, J., Washom, B., 2011. Intra-hour forecasting with a total sky imager at the UC san diego solar energy testbed. Sol. Energy 85 (11), 2881–2893.

Chu, T.-P., Jhou, J.-H., Leu, Y.-G., 2020. Image-based solar irradiance forecasting using recurrent neural networks. In: 2020 International Conference on System Science and Engineering (ICSSE). IEEE, pp. 1–4.

Coimbra, C.F., Kleissl, J., Marquez, R., 2013. Overview of solar forecasting methods and a metric for accuracy evaluation. Solar Energy Forecast. Resource Assess. 171–194.

Dahmani, K., Dizene, R., Notton, G., Paoli, C., Voyant, C., Nivet, M.L., 2014. Estimation of 5-min time-step data of tilted solar global irradiation using ANN (artificial neural network) model. Energy 70, 374–381.

de Araujo, J.M.S., 2020. Combination of WRF model and LSTM network for solar radiation forecasting—Timor Leste case study. Comput. Water Energy Environ. Eng. 9 (4), 108–144.

Dong, Z., Yang, D., Reindl, T., Walsh, W.M., 2015. A novel hybrid approach based on self-organizing maps, support vector regression and particle swarm optimization to forecast solar irradiance. Energy 82, 570–577.

Engerer, N., 2015. Minute resolution estimates of the diffuse fraction of global irradiance for southeastern Australia. Sol. Energy 116, 215–237.

Espinar, B., Aznarte, J.-L., Girard, R., Moussa, A.M., Kariniotakis, G., et al., 2010. Photovoltaic forecasting: A state of the art. In: 5th European PV-Hybrid and Mini-Grid Conference. Citeseer, pp. 250–255.

Fernández-Peruchena, C.M., Blanco, M., Gastón, M., Bernardos, A., 2015. Increasing the temporal resolution of direct normal solar irradiance series in different climatic zones. Sol. Energy 115, 255–263.

Frías-Paredes, L., Mallor, F., Gastón-Romeo, M., León, T., 2017. Assessing energy forecasting inaccuracy by simultaneously considering temporal and absolute errors. Energy Convers. Manage. 142, 533–546.

Ghimire, S., Deo, R.C., Raj, N., Mi, J., 2019. Deep solar radiation forecasting with convolutional neural network and long short-term memory network algorithms. Appl. Energy 253, 113541.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets. Adv. Neural Inf. Process. Syst. 27.

Guariso, G., Nunnari, G., Sangiorgio, M., 2020. Multi-step solar irradiance forecasting and domain adaptation of deep neural networks. Energies 13 (15), 3987.

Guermoui, M., Melgani, F., Danilo, C., 2018. Multi-step ahead forecasting of daily global and direct solar radiation: a review and case study of ghardaia region. J. Cleaner Prod. 201, 716–734.

Gueymard, C.A., 2012. Clear-sky irradiance predictions for solar resource mapping and large-scale applications: Improved validation methodology and detailed performance analysis of 18 broadband radiative models. Sol. Energy 86 (8), 2145–2169.

Guo, Z., Zhou, K., Zhang, C., Lu, X., Chen, W., Yang, S., 2018. Residential electricity consumption behavior: Influencing factors, related theories and intervention strategies. Renew. Sustain. Energy Rev. 81, 399–412.

Gutierrez-Corea, F.-V., Manso-Callejo, M.-A., Moreno-Regidor, M.-P., Manrique-Sancho, M.-T., 2016. Forecasting short-term solar irradiance based on artificial neural networks and data from neighboring meteorological stations. Sol. Energy 134, 119–131.

Hammer, A., Heinemann, D., Lorenz, E., Lückehe, B., 1999. Short-term forecasting of solar radiation: a statistical approach using satellite data. Sol. Energy 67 (1–3), 139–150.

Hargreaves, G.H., Samani, Z.A., 1982. Estimating potential evapotranspiration. J. Irrig. Drain. Div. 108 (3), 225–230.

Hassan, G.E., Youssef, M.E., Mohamed, Z.E., Ali, M.A., Hanafy, A.A., 2016. New temperature-based models for predicting global solar radiation. Appl. Energy 179, 437–450.

He, H., Lu, N., Jie, Y., Chen, B., Jiao, R., 2020. Probabilistic solar irradiance forecasting via a deep learning-based hybrid approach. IEEJ Trans. Electr. Electron. Eng. 15 (11), 1604–1612.

Heng, J., Wang, J., Xiao, L., Lu, H., 2017. Research and application of a combined model based on frequent pattern growth algorithm and multi-objective optimization for solar radiation forecasting. Appl. Energy 208, 845–866.

Hinton, G.E., Osindero, S., Teh, Y.-W., 2006. A fast learning algorithm for deep belief nets. Neural Comput. 18 (7), 1527–1554.

Hong, Y.-Y., Martinez, J.J.F., Fajardo, A.C., 2020. Day-ahead solar irradiation forecasting utilizing gramian angular field and convolutional long short-term memory. IEEE Access 8, 18741–18753.

Hong, T., Wilson, J., Xie, J., 2013. Long term probabilistic load forecasting and normalization with hourly information. IEEE Trans. Smart Grid 5 (1), 456–462.

Hu, Q., Zhang, R., Zhou, Y., 2016. Transfer learning for short-term wind speed prediction with deep neural networks. Renew. Energy 85, 83–95.

Huang, C., Wang, L., Lai, L.L., 2018. Data-driven short-term solar irradiance forecasting based on information of neighboring sites. IEEE Trans. Ind. Electron. 66 (12), 9918–9927.

Huang, X., Zhang, C., Li, Q., Tai, Y., Gao, B., Shi, J., 2020. A comparison of hour-ahead solar irradiance forecasting models based on LSTM network. Math. Probl. Eng. 2020.

Husein, M., Chung, I.-Y., 2019. Day-ahead solar irradiance forecasting for microgrids using a long short-term memory recurrent neural network: A deep learning approach. Energies 12 (10), 1856.

Hüsken, M., Stagge, P., 2003. Recurrent neural networks for time series classification. Neurocomputing 50, 223–235.

Ibrahim, I.A., Khatib, T., 2017. A novel hybrid model for hourly global solar radiation prediction using random forests technique and firefly algorithm. Energy Convers. Manage. 138, 413–425.

Ishii, K., van der Zant, T., Becanovic, V., Ploger, P., 2004. Optimization of parameters of echo state network and its application to underwater robot. In: SICE 2004 Annual Conference, vol. 3. IEEE, pp. 2800–2805.

Jaeger, H., 2001. The "echo state" approach to analysing and training recurrent neural networks-with an erratum note. Bonn, Germany: German National Research Center for Information Technology GMD Technical Report, vol 148 (34), Bonn, p. 13.

Jaeger, H., 2007. Echo state network. Scholarpedia 2 (9), 2330.

Jaeger, H., Haas, H., 2004. Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication. Science 304 (5667), 78–80.

Jaihuni, M., Basak, J.K., Khan, F., Okyere, F.G., Arulmozhi, E., Bhujel, A., Park, J., Hyun, L.D., Kim, H.T., 2020. A partially amended hybrid Bi-GRU—ARIMA model (PAHM) for predicting solar irradiance in short and very-short terms. Energies 13 (2), 435.

Jeon, B.-k., Kim, E.-J., 2020. Next-day prediction of hourly solar irradiance using local weather forecasts and LSTM trained with non-local data. Energies 13 (20), 5258.

Jiang, Y., 2008. Prediction of monthly mean daily diffuse solar radiation using artificial neural networks and comparison with other empirical models. Energy Policy 36 (10), 3833–3837.

Jiang, H., Dong, Y., Xiao, L., 2017. A multi-stage intelligent approach based on an ensemble of two-way interaction model for forecasting the global horizontal radiation of India. Energy Convers. Manage. 137, 142–154.

Justin, D., Concepcion, R.S., Calinao, H.A., Alejandrino, J., Dadios, E.P., Sybingco, E., 2020. Using stacked long short term memory with principal component analysis for short term prediction of solar irradiance based on weather patterns. In: 2020 IEEE Region 10 Conference (TENCON). IEEE, pp. 946–951.

Kaba, K., Sarıgül, M., Avcı, M., Kandırmaz, H.M., 2018. Estimation of daily global solar radiation using deep learning model. Energy 162, 126–135.

Kalogirou, S.A., 2001. Artificial neural networks in renewable energy systems applications: a review. Renew. Sustain. Energy Rev. 5 (4), 373–401.

Kanagasundaram, A., Valluvan, R., Kaneswaran, A., (2019). Solar Irradiance Forecasting using Deep Learning Approaches.

Kaushika, N., Tomar, R., Kaushik, S., 2014. Artificial neural network model based on interrelationship of direct, diffuse and global solar radiations. Sol. Energy 103, 327–342.

Kawaguchi, K., Kaelbling, L.P., Bengio, Y., 2017. Generalization in deep learning. arXiv preprint arXiv:1710.05468.

Khodayar, M., Kaynak, O., Khodayar, M.E., 2017. Rough deep neural architecture for short-term wind speed forecasting. IEEE Trans. Ind. Inf. 13 (6), 2770–2779.

Khodayar, M., Wang, J., 2018. Spatio-temporal graph deep neural network for short-term wind speed forecasting. IEEE Trans. Sustain. Energy 10 (2), 670–681.

Kumari, P., Toshniwal, D., 2019. Hourly solar irradiance prediction from satellite data using lstm.

Kumari, P., Toshniwal, D., 2020a. Impact of lockdown measures during COVID-19 on air quality–a case study of India. Int. J. Environ. Health Res. 1–8.

Kumari, P., Toshniwal, D., 2020b. Impact of lockdown on air quality over major cities across the globe during COVID-19 pandemic. Urban Clim. 34, 100719.

Kumari, P., Toshniwal, D., 2020c. Real-time estimation of COVID-19 cases using machine learning and mathematical models-the case of India. In: 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS). IEEE, pp. 369–374.

Kumari, P., Toshniwal, D., 2021a. Extreme gradient boosting and deep neural network based ensemble learning approach to forecast hourly solar irradiance. J. Cleaner Prod. 279, 123285.

Kumari, P., Toshniwal, D., 2021b. Long short term memory–convolutional neural network based deep hybrid approach for solar irradiance forecasting. Appl. Energy 295, 117061.

Kumari, P., Wadhvani, R., 2018. Wind power prediction using KLMS algorithm. In: 2018 International Conference on Inventive Research in Computing Applications (ICIRCA). IEEE, pp. 154–161.

Kwon, Y., Kwasinski, A., Kwasinski, A., 2019. Solar irradiance forecast using naïve Bayes classifier based on publicly available weather forecasting variables. Energies 12 (8), 1529.

Lago, J., De Brabandere, K., De Ridder, F., De Schutter, B., 2018. Short-term forecasting of solar irradiance without local telemetry: A generalized model using satellite data. Sol. Energy 173, 566–577.

Lee, H., Ekanadham, C., Ng, A., 2007. Sparse deep belief net model for visual area V2. Adv. Neural Inf. Process. Syst. 20, 873–880.

Li, W., Guo, D., Fang, X., 2018a. Multimodal architecture for video captioning with memory networks and an attention mechanism. Pattern Recognit. Lett. 105, 23–29.

Li, Z., Wang, K., Li, C., Zhao, M., Cao, J., 2019c. Multimodal deep learning for solar irradiance prediction. In: 2019 International Conference on Internet of Things (IThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData). IEEE, pp. 784–792.

Li, J., Ward, J.K., Tong, J., Collins, L., Platt, G., 2016. Machine learning for solar irradiance forecasting of photovoltaic system. Renew. Energy 90, 542–553.

Li, Q., Wu, Z., Ling, R., Feng, L., Liu, K., 2020a. Multi-reservoir echo state computing for solar irradiance prediction: A fast yet efficient deep learning approach. Appl. Soft Comput. 95, 106481.

Li, Q., Wu, Z., Zhang, H., 2020b. Spatio-temporal modeling with enhanced flexibility and robustness of solar irradiance prediction: a chain-structure echo state network approach. J. Cleaner Prod. 261, 121151.

Li, L., Yuan, Z., Gao, Y., 2018b. Maximization of energy absorption for a wave energy converter using the deep machine learning. Energy 165, 340–349.

Li, C., Zhang, Y., Zhao, G., Ren, Y., 2020. Hourly solar irradiance prediction using deep BiLSTM network. Earth Sci. Inform. 1–11.

Lima, F.J., Martins, F.R., Pereira, E.B., Lorenz, E., Heinemann, D., 2016. Forecast for surface solar irradiance at the Brazilian northeastern region using NWP model and artificial neural networks. Renew. Energy 87, 807–818.

Lin, X., Yang, Z., Song, Y., 2009. Short-term stock price prediction based on echo state networks. Expert Syst. Appl. 36 (3), 7313–7317.

Liu, Y., Qin, H., Zhang, Z., Pei, S., Wang, C., Yu, X., Jiang, Z., Zhou, J., 2019. Ensemble spatiotemporal forecasting of solar irradiation using variational Bayesian convolutional gate recurrent unit network. Appl. Energy 253, 113596.

Long, H., Zhang, Z., Su, Y., 2014. Analysis of daily solar power prediction with data-driven approaches. Appl. Energy 126, 29–37.

Madhiarasan, M., Deepa, S., 2016. Deep neural network using new training strategy based forecasting method for wind speed and solar irradiance forecast. Middle-East J. Sci. Res. 24 (12), 3730–3747.

McCandless, T., Haupt, S., Young, G., 2016. A regime-dependent artificial neural network technique for short-range solar irradiance forecasting. Renew. Energy 89, 351–359.

Mecibah, M.S., Boukelia, T.E., Tahtah, R., Gairaa, K., 2014. Introducing the best model for estimation the monthly mean daily global solar radiation on a horizontal surface (case study: Algeria). Renew. Sustain. Energy Rev. 36, 194–202.

Miller, S.D., Rogers, M.A., Haynes, J.M., Sengupta, M., Heidinger, A.K., 2018. Short-term solar irradiance forecasting via satellite/model coupling. Sol. Energy 168, 102–117.

Mishra, M., Dash, P.B., Nayak, J., Naik, B., Swain, S.K., 2020. Deep learning and wavelet transform integrated approach for short-term solar PV power prediction. Measurement 166, 108250.

Mishra, A., Kaushika, N., Zhang, G., Zhou, J., 2008. Artificial neural network model for the estimation of direct solar radiation in the Indian zone. Int. J. Sustain. Energy 27 (3), 95–103.

Mishra, S., Palanisamy, P., 2018. Multi-time-horizon solar forecasting using recurrent neural network. In: 2018 IEEE Energy Conversion Congress and Exposition (ECCE). IEEE, pp. 18–24.

Mishra, S., Palanisamy, P., 2019. An integrated multi-time-scale modeling for solar irradiance forecasting using deep learning. arXiv preprint arXiv:1905.02616.

Moreno-Munoz, A., De la Rosa, J., Posadillo, R., Bellido, F., 2008. Very short term forecasting of solar radiation. In: 2008 33rd IEEE Photovoltaic Specialists Conference. IEEE, pp. 1–5.

Muhammad, A., Lee, J.M., Hong, S.W., Lee, S.J., Lee, E.H., 2019. Deep learning application in power system with a case study on solar irradiation forecasting. In: 2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC). IEEE, pp. 275–279.

Mukherjee, A., Ain, A., Dasgupta, P., 2018. Solar irradiance prediction from historical trends using deep neural networks. In: 2018 IEEE International Conference on Smart Energy Grid Engineering (SEGE). IEEE, pp. 356–361.

Mukhoty, B.P., Maurya, V., Shukla, S.K., 2019. Sequence to sequence deep learning models for solar irradiation forecasting. In: 2019 IEEE Milan PowerTech. IEEE, pp. 1–6.

Nann, S., Riordan, C., 1991. Solar spectral irradiance under clear and cloudy skies: Measurements and a semiempirical model. J. Appl. Meteorol. Climatol. 30 (4), 447–462.

Nonnenmacher, L., Coimbra, C.F., 2014. Streamline-based method for intra-day solar forecasting through remote sensing. Sol. Energy 108, 447–459.

Notton, G., Nivet, M.-L., Voyant, C., Paoli, C., Darras, C., Motte, F., Fouilloy, A., 2018. Intermittent and stochastic character of renewable energy sources: Consequences, cost of intermittence and benefit of forecasting. Renew. Sustain. Energy Rev. 87, 96–105.

Obiora, C.N., Ali, A., Hasan, A.N., 2020. Forecasting hourly solar irradiance using long short-term memory (LSTM) network. In: 2020 11th International Renewable Energy Congress (IREC). IEEE, pp. 1–6.

Ogawa, A., Hori, T., 2017. Error detection and accuracy estimation in automatic speech recognition using deep bidirectional recurrent neural networks. Speech Commun. 89, 70–83.

Ögelman, H., Ecevit, A., Tasdemiroğlu, E., 1984. A new method for estimating solar radiation from bright sunshine data. Sol. Energy 33 (6), 619–625.

Olatomiwa, L., Mekhilef, S., Shamshirband, S., Mohammadi, K., Petković, D., Sudheer, C., 2015. A support vector machine–firefly algorithm-based model for global solar radiation prediction. Sol. Energy 115, 632–644.

Opitz, D., Maclin, R., 1999. Popular ensemble methods: An empirical study. J. Artificial Intelligence Res. 11, 169–198.

Ozgoren, M., Bilgili, M., Sahin, B., 2012. Estimation of global solar radiation using ANN over Turkey. Expert Syst. Appl. 39 (5), 5043–5051.

Pang, Z., Niu, F., O'Neill, Z., 2020. Solar radiation prediction using recurrent neural network and artificial neural network: A case study with comparisons. Renew. Energy 156, 279–289.

Pasupa, K., Sunhem, W., 2016. A comparison between shallow and deep architecture classifiers on small dataset. In: 2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE). IEEE, pp. 1–6.

Pazikadin, A.R., Rifai, D., Ali, K., Malik, M.Z., Abdalla, A.N., Faraj, M.A., 2020. Solar irradiance measurement instrumentation and power solar generation forecasting based on artificial neural networks (ANN): A review of five years research trend. Sci. Total Environ. 715, 136848.

Peng, T., Zhang, C., Zhou, J., Nazir, M.S., 2021. An integrated framework of bi-directional long-short term memory (BiLSTM) based on sine cosine algorithm for hourly solar radiation forecasting. Energy 119887.

Perez, R., Kivalov, S., Schlemmer, J., Hemker Jr, K., Renné, D., Hoff, T.E., 2010. Validation of short and medium term operational solar radiation forecasts in the US. Sol. Energy 84 (12), 2161–2172.

Prado-Rujas, I.-I., García-Dopico, A., Serrano, E., Pérez, M.S., 2021. A flexible and robust deep learning-based system for solar irradiance forecasting. IEEE Access 9, 12348–12361.

Qiao, J., Wang, G., Li, W., Li, X., 2018. A deep belief network with PLSR for nonlinear system modeling. Neural Netw. 104, 68–79.

Qing, X., Niu, Y., 2018. Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM. Energy 148, 461–468.

Rahman, A., Srikumar, V., Smith, A.D., 2018. Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. Appl. Energy 212, 372–385.

Reikard, G., 2009. Predicting solar radiation at high resolutions: A comparison of time series forecasts. Sol. Energy 83 (3), 342–349.
Royer, J.C., Wilhelm, V.E., Junior, L.A.T., Franco, E.M.C.n., 2016. Short-term solar radiation forecasting by using an iterative combination of wavelet artificial neural networks. Indep. J. Manage. Prod. 7 (1), 271–288.
Samuel, T., 1991. Estimation of global radiation for Sri Lanka. Sol. Energy 47 (5), 333–337.
Schuster, M., Paliwal, K.K., 1997. Bidirectional recurrent neural networks. IEEE Trans. Signal Process. 45 (11), 2673–2681.
Şen, Z., 2004. Solar energy in progress and future research trends. Prog. Energy Combust. Sci. 30 (4), 367–416.
Shaddel, M., Javan, D.S., Baghernia, P., 2016. Estimation of hourly global solar irradiation on tilted absorbers from horizontal one using artificial neural network for case study of Mashhad. Renew. Sustain. Energy Rev. 53, 59–67.
Sharda, S., Singh, M., Sharma, K., 2020. RSAM: Robust self-attention based multi-horizon model for solar irradiance forecasting. IEEE Trans. Sustain. Energy.
Sharma, V., Yang, D., Walsh, W., Reindl, T., 2016. Short term solar irradiance forecasting using a mixed wavelet neural network. Renew. Energy 90, 481–492.
Siddiqui, T.A., Bharadwaj, S., Kalyanaraman, S., 2019. A deep learning approach to solar-irradiance forecasting in sky-videos. In: 2019 IEEE Winter Conference on Applications of Computer Vision (WACV). IEEE, pp. 2166–2174.
SOLARGIS, 2019. The World Bank, Source: Global Solar Atlas 2.0, Solar resource data: Solargis, https://solargis.com/maps-and-gis-data/download/world.
Song, Z., Brown, L.E., 2019. Multi-dimensional evaluation of temporal neural networks on solar irradiance forecasting. In: 2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia). IEEE, pp. 4192–4197.
Song, K., Yao, T., Ling, Q., Mei, T., 2018. Boosting image sentiment analysis with visual attention. Neurocomputing 312, 218–228.
Sorkun, M.C., Paoli, C., Incel, O.D., 2017. Time series forecasting on solar irradiation using deep learning. In: 2017 10th International Conference on Electrical and Electronics Engineering (ELECO). IEEE, pp. 151–155.
Srivastava, S., Lessmann, S., 2018. A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data. Sol. Energy 162, 232–247.
Sun, S., Chen, W., Wang, L., Liu, X., Liu, T.-Y., 2016. On the depth of deep neural networks: A theoretical view. In: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 30, p. 1.
Sun, S., Wang, S., Zhang, G., Zheng, J., 2018. A decomposition-clustering-ensemble learning approach for solar radiation forecasting. Sol. Energy 163, 189–199.
Voyant, C., Notton, G., Kalogirou, S., Nivet, M.-L., Paoli, C., Motte, F., Fouilloy, A., 2017. Machine learning methods for solar radiation forecasting: A review. Renew. Energy 105, 569–582.
Wang, Z., Hong, T., Piette, M.A., 2020. Building thermal load prediction through shallow machine learning and deep learning. Appl. Energy 263, 114683.
Wang, H., Ruan, J., Wang, G., Zhou, B., Liu, Y., Fu, X., Peng, J., 2018a. Deep learning-based interval state estimation of AC smart grids against sparse cyber attacks. IEEE Trans. Ind. Inf. 14 (11), 4766–4778.
Wang, Y., Shen, Y., Mao, S., Chen, X., Zou, H., 2018b. LASSO And LSTM integrated temporal model for short-term solar intensity forecasting. IEEE Internet Things J. 6 (2), 2933–2944.
Wang, Z., Tian, C., Zhu, Q., Huang, M., 2018c. Hourly solar radiation forecasting using a volterra-least squares support vector machine model combined with signal decomposition. Energies 11 (1), 68.
Wang, Z., Wang, Y., Zeng, R., Srinivasan, R.S., Ahrentzen, S., 2018d. Random forest based hourly building energy prediction. Energy Build. 171, 11–25.
Wang, F., Yu, Y., Zhang, Z., Li, J., Zhen, Z., Li, K., 2018e. Wavelet decomposition and convolutional LSTM networks based improved deep learning model for solar irradiance forecasting. Appl. Sci. 8 (8), 1286.
Wang, F., Zhang, Z., Chai, H., Yu, Y., Lu, X., Wang, T., Lin, Y., 2019a. Deep learning based irradiance mapping model for solar PV power forecasting using sky image. In: 2019 IEEE Industry Applications Society Annual Meeting. IEEE, pp. 1–9.
Wang, F., Zhang, Z., Liu, C., Yu, Y., Pang, S., Duić, N., Shafie-Khah, M., Catalão, J.a.P., 2019b. Generative adversarial networks and convolutional neural networks based weather classification model for day ahead short-term photovoltaic power forecasting. Energy Convers. Manage. 181, 443–462.
Wang, W., Zhen, Z., Li, K., Lv, K., Wang, F., 2019c. An ultra-short-term forecasting model for high-resolution solar irradiance based on SOM and deep learning algorithm. In: 2019 IEEE Sustainable Power and Energy Conference (ISPEC). IEEE, pp. 1090–1095.
Wang, F., Zhen, Z., Liu, C., Mi, Z., Shafie-khah, M., Catalão, J.a.P., 2018f. Time-section fusion pattern classification based day-ahead solar irradiance ensemble forecasting model using mutual iterative optimization. Energies 11 (1), 184.
Wang, F., Zhen, Z., Mi, Z., Sun, H., Su, S., Yang, G., 2015. Solar irradiance feature extraction and support vector machines based weather status pattern recognition model for short-term photovoltaic power forecasting. Energy Build. 86, 427–438.
Wojtkiewicz, J., Hosseini, M., Gottumukkala, R., Chambers, T.L., 2019. Hour-ahead solar irradiance forecasting using multivariate gated recurrent units. Energies 12 (21), 4055.
Yadav, A.K., Chandel, S., 2014. Solar radiation prediction using artificial neural network techniques: A review. Renew. Sustain. Energy Rev. 33, 772–781.
Yagli, G.M., Yang, D., Srinivasan, D., 2019. Automatic hourly solar forecasting using machine learning models. Renew. Sustain. Energy Rev. 105, 487–498.
Yan, K., Shen, H., Wang, L., Zhou, H., Xu, M., Mo, Y., 2020. Short-term solar irradiance forecasting based on a hybrid deep learning methodology. Information 11 (1), 32.
Yang, D., Jirutitijaroen, P., Walsh, W.M., 2012. Hourly solar irradiance time series forecasting using cloud cover index. Sol. Energy 86 (12), 3531–3543.
Yang, D., Ye, Z., Lim, L.H.I., Dong, Z., 2015. Very short term irradiance forecasting using the lasso. Sol. Energy 114, 314–326.
Yeom, J.-M., Deo, R.C., Adamowski, J.F., Park, S., Lee, C.-S., 2020. Spatial mapping of short-term solar radiation prediction incorporating geostationary satellite images coupled with deep convolutional LSTM networks for South Korea. Environ. Res. Lett. 15 (9), 094025.
Yu, Y., Cao, J., Zhu, J., 2019. An LSTM short-term solar irradiance forecasting under complicated weather conditions. IEEE Access 7, 145651–145666.
Yu, C., Li, Y., Bao, Y., Tang, H., Zhai, G., 2018. A novel framework for wind speed prediction based on recurrent neural networks and support vector machine. Energy Convers. Manage. 178, 137–145.
Zang, H., Cheng, L., Ding, T., Cheung, K.W., Wang, M., Wei, Z., Sun, G., 2020a. Application of functional deep belief network for estimating daily global solar radiation: A case study in China. Energy 191, 116502.
Zang, H., Liu, L., Sun, L., Cheng, L., Wei, Z., Sun, G., 2020b. Short-term global horizontal irradiance forecasting based on a hybrid CNN-LSTM model with spatiotemporal correlations. Renew. Energy 160, 26–41.
Zendehboudi, A., Baseer, M., Saidur, R., 2018. Application of support vector machine models for forecasting solar and wind energy resources: A review. J. Cleaner Prod. 199, 272–285.
Zhang, C.-Y., Chen, C.P., Gan, M., Chen, L., 2015. Predictive deep Boltzmann machine for multiperiod wind speed forecasting. IEEE Trans. Sustain. Energy 6 (4), 1416–1425.
Zhang, W., Luo, Y., Zhang, Y., Srinivasan, D., 2020. Solargan: Multivariate solar data imputation using generative adversarial network. IEEE Trans. Sustain. Energy 12 (1), 743–746.
Zhang, J., Zhao, L., Deng, S., Xu, W., Zhang, Y., 2017. A critical review of the models used to estimate solar radiation. Renew. Sustain. Energy Rev. 70, 314–329.
Zhao, X., Wei, H., Wang, H., Zhu, T., Zhang, K., 2019. 3D-CNN-based feature extraction of ground-based cloud images for direct normal irradiance prediction. Sol. Energy 181, 510–518.
Ziyabari, S., Du, L., Biswas, S., 2020. A spatio-temporal hybrid deep learning architecture for short-term solar irradiance forecasting. In: 2020 47th IEEE Photovoltaic Specialists Conference (PVSC). IEEE, pp. 0833–0838.