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Creating an artificial neural network time series model for the prediction of daily solar radiation in Oran

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ABSTRACT

Water and clean energies are currently a major scientific and political concern. The use of numerical prediction is often recommended in these areas, for optimal exploitation of renewable energy resources, mainly for seawater desalination and other energy and food security activities. In this study, we present an application of artificial neural networks (ANN), developed for daily solar energy forecasting. The ANN model developed is based on the multi-layer perceptron, the most widely used ANN type in renewable energy and time series forecasting. The developed model has two main properties: I. The ANN training is based on long-term reanalysis data, allowing the model to be trained even in areas where no radiation measurements are available, as is the case for marine areas and in the new desalination plants. II. The model allows automatic selection of the optimal ANN model architecture based on the training data. A thirty-nine-year time series of reanalysis data between 1980 and 2018 was used for training and model implementation. Thus, the model accuracy was evaluated based on one-year data (2019). The obtained error analysis results show that the developed model has a good performance in line with previous studies. The developed ANN models are characterized by reasonable daily prediction accuracy, with a root mean square error of 3.248 MJ/(m^2 d) for solar radiation prediction. This verifies the accuracy and ability of the model to predict solar radiation to ensure optimal management of solar energy farms.

Keywords: Artificial neural networks; Multi-layer perceptron; ANN time series model; Renewable energies; Daily forecast

1. Introduction

Prediction is an essential task in many fields: economics, meteorology, energies, water resources, etc. It refers to a process that seeks to estimate the values of one or more variables at a given time in the future. The growing interest and demand for energy and clean energy have led to an acceleration of research related to the evaluation and prediction of solar radiation [1–4] and other energy sources [5,6]. solar radiation prediction is essential in renewable energy applications, for example, for the dimensioning of photovoltaic systems [7]. Accurate prediction or measurement of solar radiation time series data is considered the first step in assessing solar energy availability. Solar

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radiation measurements are rare and unavailable at most sites, but, they are estimated at other locations where there is no equipment [8–10]. Therefore, for the development of daily forecasting models of solar energy resources, a recourse to reanalysis data can be necessary for areas where solar radiation measurements are not available. The prediction of climatic indicators such as wind speed and direct solar radiation is recommended for optimal management of wind and solar energy resources [11]. Therefore, an accurate daily power generation forecasting model may be necessary. Indeed, power plant operators and photovoltaic producers need to accurately forecast the amount of energy that will be available when operating their solar power plants [12,13]. An accurate daily power generation forecasting model is essential for the operation of supply companies. Among prediction techniques used to estimate solar radiation: the stochastic methods [14], the analytical methods [15], Markov chains [16,17], and one of the prediction approaches followed recently is the artificial intelligence technique by artificial neural networks (ANN) [18–20], it is the subject of this study. ANN is one of the most effective and popular methods in the field of renewable energy and the prediction of meteorological data such as solar radiation [18,21–24]. This method has been used in various prediction applications, including solar radiation prediction, with one of the highest levels of success. The study by Mubiru and Banda [23] shows that ANNs are more accurate compared to empirical methods in estimating global solar radiation; this is because the neural network responds to the nonlinear and non-stationary nature of solar radiation [25]. An accurate daily forecast of these last parameters allows making necessary decisions for the optimal exploitation of renewable energy resources. The neural networks most adapted to daily forecasting based on time series data are of the multi-layer perceptron (MLP) form [26]. The latter is the most used in the field of renewable energies, in particular solar radiation [18]. An optimized MLP with endogenous inputs can predict solar radiation with acceptable errors [27–29], moreover, the MLP performs well in learning complex relationships and various computational structures. Therefore, it is considered a good tool for the prediction of time-series data [30]. The main objective of this study is the implementation of an ANN model for daily solar radiation forecasting based on solar radiation time series data. The developed model allows to train the ANN-based on reanalysis data; the use of the latter allows training of the model in areas where radiation measurements are unavailable. A situation often encountered in the new installations of desalination plants and solar energy farms. The "water-energy" nexus is highly relevant for several countries, especially for wastewater treatment, or for seawater desalination. The combination of renewable energy, such as wind, solar and geothermal energy, to desalination systems holds great promise for improving the drinking water supply in water-scarce regions [31–33]. The integration of renewable resources in desalination is becoming more and more attractive. This combination makes it possible to increase the volume of water treated in desalination plants powered by solar energy, directly or indirectly [34]. This is justified by the fact that this combination will allow countries to address water scarcity problems with a clean energy source that does not cause atmospheric pollution and does not affect the global climate and at low operating and maintenance costs [35]. The input data considered in the model training are given with high accuracy, provided by the National Aeronautics and Space Administration (NASA); "the Modern-Era Retrospective analysis for Research and Applications Version 2" (MERRA-2) [36]. The particularity of this study consists in the development of an ANN model based on these reanalysis data (MERRA-2), due to the absence of experimental solar radiation in the Algerian Coasts and sea. MERRA-2 covers the whole Algerian territory and all the globe. The use of reanalysis data is the alternative for the development of ANN models in areas where meteorological measurements are absent or only available over a short period. The developed model was evaluated at Oran in northwest Africa, which is a coastal area characterized by a semi-arid Mediterranean climate. In addition, the developed ANN model can also be used to estimate missing daily data due to the malfunctioning of already installed measuring devices. The ANN model accuracy was evaluated against one year of daily solar radiation reanalysis, and the error statistics were presented. It should be noted that the accuracy of the developed ANN model may also depend on the quantity and quality of the data used to train the models; it may also depend on the climate variability in the study area. Independent validation at each area of interest remains necessary.

2. Methodology

2.1. Data description

As already mentioned in the introduction section, the ANN model developed in this work aim to predict daily solar radiation based on time series data. Given the spatial limitation of meteorological stations [37], and especially those with solar radiation sensors, this model was developed to be operational with spatial reanalysis data from the second and final version of MERRA-2 [38] provided by NASA. MERRA-2 was created to replace the old MERRA reanalysis and to resolve the limitations of the latter in assimilating the most recent sources of satellite data. These reanalyzed data are free of charge at (https://gmao.gsfc.nasa.gov/reanalysis/merra-2/). MERRA-2 is a data collection that includes many climate variables such as temperature, solar radiation, wind speed, precipitation, and other types of meteorological data. MERRA-2 provides an ongoing near-real-time climate reanalysis and includes aerosol data assimilation, allowing for a multi-decadal reanalysis in which aerosol and meteorological observations are assimilated together in a global data assimilation system. These data are characterized by a spatial resolution of 0.625°Lon × 0.5°Lat with a total of 576 points in longitude and 361 points in latitude. The temporal resolution of the dataset is 1 h [39], and the output data files are provided in netCDF-4 format [40]. MERRA-2 covers a period from 1980 to the present. These data were evaluated and validated by [41] with respect to data from measuring stations of meteorological institutions such as Meteonorm and Deutscher Wetterdienst (DWD, or German

National Weather Service). In this study, the ANN model was developed for the daily forecast of the SWGDN, surface incident shortwave flux: incident solar radiation (from 0.175 to 3.85 microns) at the surface, all-sky, clear-sky conditions, and top of the atmosphere. SWGDN is a valuable parameter in the development of solar renewable energy [42] and is rarely measured at weather stations [43]. The reanalysis data present the first alternative in the absence of the experimental data. The development of ANN models from time series in regions where measurement data are absent or cover a short period is impossible without the use of data reanalysis. The present model is developed to address this issue.

2.2. Time series

Time series is a collection of data that are typically sampled equally over time intervals [44] a succession of observations (x_0, x_1, … , x_n) representing phenomena over time. Typically, in a time series, the set of observations x_t are organized in chronological order, and each observation is associated with a single specific time instant t [45].

2.3. Artificial neural network

An artificial neural network (ANN) is an intelligent operating system designed to learn, remember, and create connections between data. It is used to solve complex problems in many applications such as prediction, modeling, clustering, pattern recognition, optimization, curve fitting and regression [46], etc. The structure of the ANN is composed of a succession of layers: the input layer, which contains the collected data, an output layer that produces computed information, and one or more hidden layers allowing to link the input and output layers [47]. The neuron is the basic processing unit of a neural network and performs two functions: collecting inputs and producing outputs. Therefore, neurons are primarily mathematical operators, and from a mathematical point of view, formal neurons have a linear algebraic function parameterized that it is then taken as an argument of a transfer function f to form the output y [48,49] represented by:

$$y = f\left(x_1, x_2, \ldots, x_n; w_{i1}, w_{i2}, \ldots, w_{in}\right) \quad (1)$$

where $\{x_j\}$ are inputs and $\{w_{ij}\}$ are parameters of the weight of layer i and y is the output. The inputs can be binary (0,1), real or bipolar (–1,1) [50,51]. Typically, an ANN is composed of simple processing units; the neurons are networked via a large number of weighted links. The latter store the acquired knowledge, and signals or information can be transmitted via these links. An input x_j is passed through a connection, which multiplies its strength by a weight w_{ij} to give a product $x_j w_{ij}$ and the neuron's bias b_j. This product is an argument for an activation or transfer function f, which gives an output y_i represented by:

$$y_i = f\left(s_i\right) \quad (2)$$

where

$$s_i = \sum_{j=1}^{n} x_j w_{ij} + b_i \quad (3)$$

And i is an index of the hidden layer neurons, and j is an index of an input to the neural network [21,52]. Fig. 1 shows the layout of a basic artificial neuron. In its simple form, each neuron is linked to the other neurons of the previous layer by adaptive synaptic weights [53]. The knowledge is usually saved in the form of a set of connection weights. The advantage of ANN techniques is that they do not require the knowledge of mathematical calculations between parameters, but they involve less computational effort and provide a compact solution for multi-variable problems.

The multi-layer perceptron is a linear formal neural network classifier in the form of multiple layers [48] (composed of a succession of layers), where information flows only from the input layer to the output layer, as shown in Fig. 2.

2.4. MLP time series

In this section, we present an overview of the application of MLP methodology in the context of time series models. In recent years, artificial neural networks have been applied to many domains for time series prediction [10,25,45,54,55]. Since MLP can model both linear and non-linear time series structures, it can also perform better than other methods [56]. Prediction of future values of a time series of the data based on past values is performed using prediction models. To make the prediction, a fixed number "p" of past values are defined as inputs to the MLP, the output being the prediction of the future value of the time series [54]. Fig. 3 shows the basic architecture of an

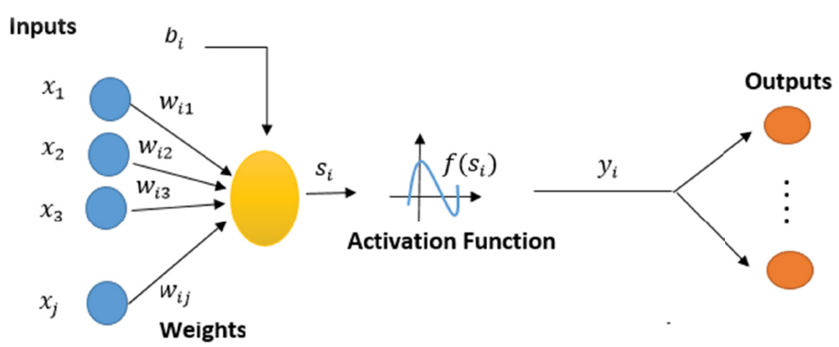

Fig. 1. Presentation of basic neural networks.

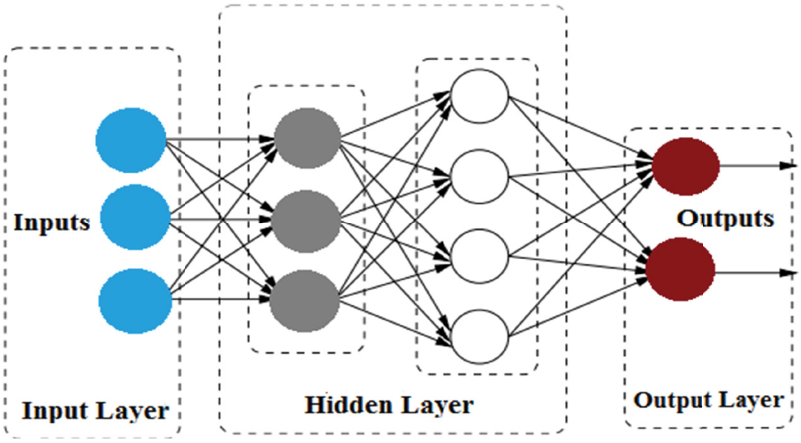

Fig. 2. Presentation of the perceptron multilayer neural network.

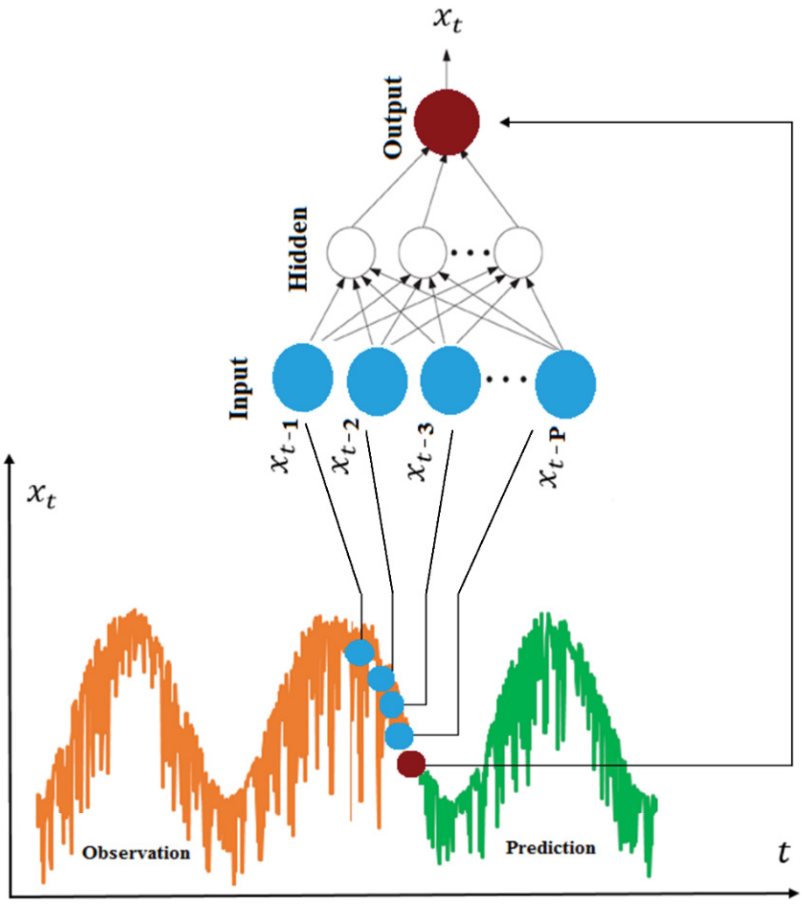

Fig. 3. Presentation of the application of MLP to time series forecasting (bias nodes are not displayed).

MLP application for forecasting time series data during the learning task. When modeling time series, we do not have all of the information that would be needed to make fine-grained predictions. However, by using the history we have and combining all this information, we can significantly reduce the margin of error of our forecasts.

3. Processing the MLP time series

The main objective of this work is the implementation of a daily forecast ANN model using solar radiation time series data. This model was developed using a variety of different open-source technologies, including Java Enterprise Edition (JEE) (http://java.sun.com/javaee/) and

PostgreSQL (https://www.postgresql.org): which is one of the leading Relational Data Base Management Systems (RDBMS) on the market. The algorithm of the present study includes codes that allow the automatic development of ANN model of daily forecast based on solar radiation time series inputs. Our methodology aims at using the solar radiation time series formalism with MLP. The main parameters that influence the complexity of the network architecture and its training are the number of input data (the neurons that represent the input layer of the network), the number of hidden layers and their number of neurons, the activation (or transfer) function, the training and the comparison function used during the training phase. In summary, the classic ANN development cycle consists of four main areas: a. Data collection, b. MLP implementation, c. Selection of the optimal architecture.

3.1. Data collection

The time series of daily solar radiation data having the unit MJ/m^2 d, for a period of 39 y, from 1980 to 2019 were collected and managed using PostgreSQL. For the development of the ANN model (training, validation, and testing), we build a database composed of (13,870 d × 6 inputs). After building the database, we proceed with automatic and random separation phase input/target data into three sets: one set is built to perform the learning, the other for the validation, which allows controlling the learning phase, and another to test the obtained network and determine its performance. In the present work, the training set, which consists of 80% of the dataset (10,950 d × 6 inputs), was used for computing the gradient and updating the network weights and biases, while 10% of the dataset (1,460 d × 6 inputs) was used as validation dataset and 10% as test dataset (1,460 d × 6 inputs). The use of reanalysis data for ANN models may be more advantageous spatially and temporally, but it should be noted that if experimental measurement data were available over a significant period of time, their accuracy would be even more reliable.

3.2. MLP implementation

In the present work, the ANN model was developed based on a three-layer network with a sigmoid activation function in the hidden layers. To show how this works, the neural network was trained with the previously mentioned data from an initial date to a final date to predict the value of the subsequent final date. As a strategy, we take the sequences of p days (x_t, x_{t-1}, …, x_{t-p}) to predict each (x_{t+1}) day. In the training set, the (x_{t+1}) day is the supervised value, a fixed number p of past time series values are defined as MLP inputs, and the outputs are the future time series data values x_{t+1}. In this case, the number of inputs, as well as the number of outputs of the ANN, were chosen; solar radiation over a period of 6 d preceding the day to be predicted was considered on the input layer (X_t, …, X_{t-5}) normalized to [0;1], to predict each X_{t+1} day, in the learning set, so the 7th day corresponds to the supervised output value. Prior to any training, it is recommended to normalize the input and target values. In this case, the input and output data are pretreated by performing a linear normalization between 0 and 1 ([0,1]), with respect to their minimum or maximum value. The following normalization equation was applied:

$$N(E) = \frac{E - \text{Min}}{\text{Max} - \text{Min}} \quad (4)$$

where $N(E)$ is the normalized value, E is the raw value, Min is the minimum value recorded on this database and Max is the maximum value recorded on this database. The solar radiation time series data for the years between 1980 and 2018 were normalized s and divided into three sets as already specified in the Data Collection section. The training set and the validation set constitute the major part of the data, because, from these data sets, the connection weights of the neurons are adjusted during the training. The latter consists in calculating the optimal weights of the different connections, in order to acquire the knowledge of the network. On the other hand, the validation set is used to check the generalization capacity of the network and to stop the training. The purpose of this training is to allow the neural network to learn from historical examples. If the training is done correctly, the network can provide an output response that is very close to the original value of the training dataset. In other words, the artificial neural network model should be able to predict the new data (which is not part of the training set) with minimal error. Once the training of the network is completed, tests must still be performed to estimate its generalization quality, and this is done by presenting it with a different database than the ones used for training or validation. The test set is used to evaluate the performance of the out-of-sample neural network and its generalization ability.

3.3. Selection of the optimal architecture

It is very complicated to select the number of neurons in a hidden layer and to choose the number of hidden layers for any artificial neural network model. There is currently no theoretical method for selecting the optimal architecture of a time series ANN network. Indeed, the optimal values of the number of hidden neurons correspond to the minimum of the obtained generalization error. The most efficient way to define the architecture of the model is to test a large number of possible architectures and to choose the most efficient one. In order to find the optimal performance of these models, training was performed by increasing the number of hidden layers one by one until the third layer and the same for the number of neurons in a hidden layer one by one until the 107th neuron. The ANN models developed in this work were performed by the back-propagation algorithm [57] with the sigmoidal non-linear transfer function for the hidden layers. This function is represented by:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (5)$$

4. Model accuracy assessment

The data considered for the model accuracy assessment was not used for the ANN model development and covers the year 2019. The evaluation process consisted of comparing the daily solar radiation estimated using the developed ANN model against the validated reanalysis data. Two error parameters were computed to evaluate the model performance; for the mean absolute error (MAE), and the root mean square error (RMSE),

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - O_i\right| \tag{6}$$

where MAE is the mean absolute error, it is defined as a quantity that is used to measure the proximity between the predicted values and the measured values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_i - O_i\right)^2} \tag{7}$$

where RMSE is the root mean square error. It indicates the level of dispersion of the ANN model results. N is the total number of observations, O_i and P_i are respectively the observed solar radiation and the data predicted by the neural network.

5. Results and discussion

In this section, we present the results obtained after training the ANN model and the results of the application and validation of the model in a reference station in the city of Oran (35.63° N 0.60° W). The time series from MERRA-2 solar radiation re-analysis data was used for the development of the model. This time series covers a period of 39 y, from January 1980 to December 2019. Thus, the data of 2019 have been used to test the developed forecast model, as previously mentioned. The model implemented has been trained and can predict the daily solar reasoning from input data that consists of a time series of solar radiation observations during the 6 d preceding the day to predict.

5.1. ANN architecture and model training

Parameters used for training the ANN model in the reference station at Oran are shown in Table 1. The iteration was fixed to 1,000. The learning rate and momentum factor were fixed and were to be 0.01 and 0.7, respectively.

The number of hidden layers and the number of neurons in the hidden layer corresponding to the lowest mean square error are defined as the optimal architecture of the daily solar radiation forecast model. Fig. 4 shows the RMSEs as a function of the number of hidden layers and the number of neurons in each hidden layer and covers the set of architectures evaluated for the ANN model during training.

Fig. 4 clearly shows a variation in the performance of the model as a function of the architecture, and it allows us to define the optimal architecture, which corresponds to the lowest value of RMSEs, namely 3.32 MJ/(m^2 d). The latter corresponds to 2 hidden layers with 65 neurons. Table 2 shows some error statistics (RMSE and MAE) for the nine ANN model architectures that correspond to the lowest RMSE values.

Table 1
Performance parameters used for training

Performance parameters	Value
Number of input	6 (solar radiation value of the last 6 d)
Number of output	1 (solar radiation value of the next day)
Number of hidden layers	1–3
Neurons by layer	1–107
Learning rate	0.01
Maximum iteration	1,000
Momentum	0.7

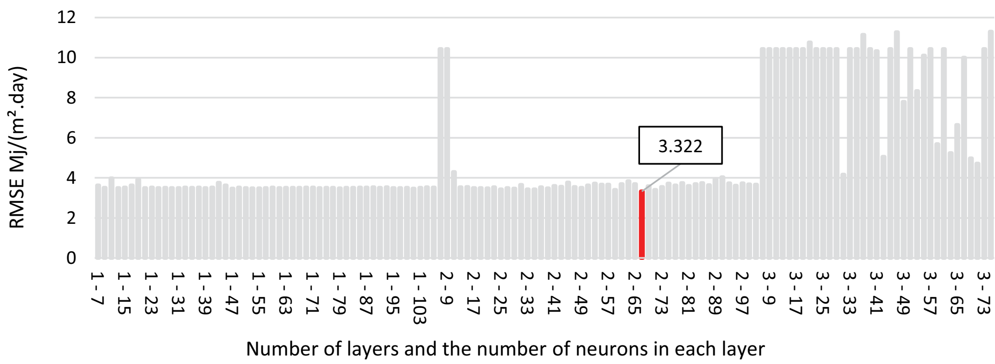

Fig. 4. The RMSE according to the number of hidden layers and the number of neurons in each hidden layer (the red bar corresponds to the lowest RMSE).

Regarding the error statistics recorded for the ANN model; the minimum values of RMSE and MAE obtained during the training of the ANN model are 3.321 and 2.585 MJ/(m^2 d) successively.

5.2. Daily predicted results and accuracy

For the evaluation and testing of the developed model, we used data covering the period from January 2019 to December 2019 (data not used during ANN model training). During this period, the solar radiation of 359 d was predicted using the ANN model. Fig. 5 shows a plot of predicted solar radiation time series compared to solar radiation based on reanalyzed NASA data. This figure shows that the model performs well in predicting daily solar radiation but with poor performance in estimating abrupt decreases that may be related to abrupt increases in cloud cover.

Nevertheless, the performance of the model is considered good regarding the error statistics considered low for such a forecast. The RMSE during the validation period is 3.248 MJ/(m^2 d) (Table 3).

These results of the error statistics are compared with the results obtained for models developed recently by other previous studies [54,58,59], and reflect a very good performance of the ANN model developed during this study. As an example, the daily solar radiation forecasting ANN time series model developed by [54] at Ajaccio station (France), had an RMSE of 3.59 MJ/(m^2 d), and an RMSE of 8.41 MJ/(m^2 d) is obtained for another daily solar radiation forecast ANN model developed by [58] at Al-Madinah station (Saudi Arabia) by considering several meteorological parameters as input data [59]. They also obtained an RMSE of 3.76 MJ/(m^2 d) for their model at the Castilla y León Region (Spain) stations is also in line with the RMSE obtained in the present study; this reflects that the developed model is endowed with a good accuracy in the daily prediction of solar radiation. The scatter plot (Fig. 6) also shows a weak distribution and linearity

Table 3
Error statistics obtained for the ANN model for training and validation

Model	Training		Validation	
	RMSE	MAE	RMSE	MAE
	MJ/(m^2 d))	MJ/(m^2 d))	MJ/(m^2 d)	MJ/(m^2 d)
ANN	3.321	2.585	3.248	2.500

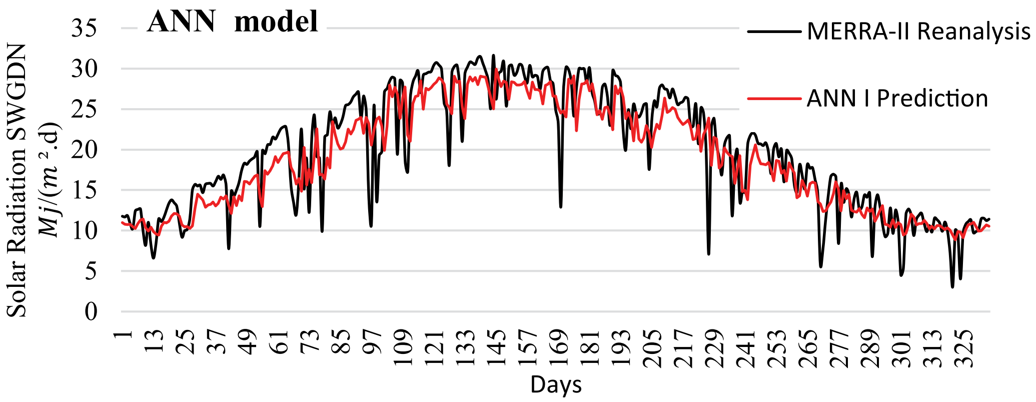

Fig. 5. SWGDN solar radiation prediction time curve predicted by the ANN model compared to the SWGDN of MERRA-2.

Table 2
Error statistics for nine different architectures of the ANN model

ANN architectures					
Input	Layer	Neurons by layer	Output	MAE MJ/(m^2 d)	RMSE MJ/(m^2 d)
6	1	7	1	2.890	3.614
6	1	51	1	2.770	3.468
6	1	107	1	2.280	3.515
6	2	11	1	3.565	4.293
6	2	67	1	2.585	3.321
6	2	101	1	2.994	3.663
6	3	23	1	8.431	10.429
6	3	51	1	8.432	10.430
6	3	71	1	3.900	4.716

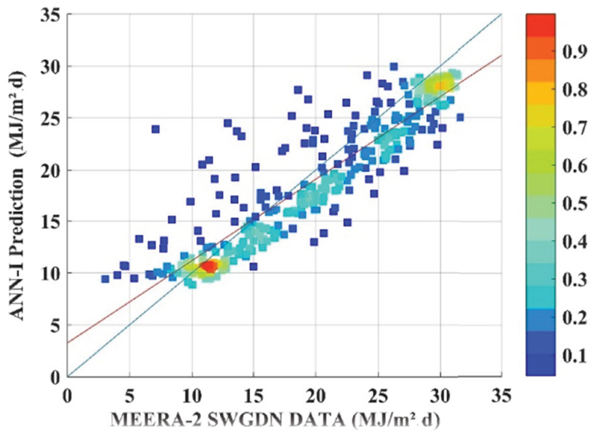

Fig. 6. Scatter plot of the daily estimated SWGDN using ANN model against daily SWGDN reanalysis. The color bar indicates the normalized density of daily estimations in the scatter plotter.

between the predicted data and the MERRA-2 reanalysis data, with a tendency to slightly underestimate the strong values above 20 MJ/(m^2 d) and slightly underestimate the values below 15 MJ/(m^2 d).

6. Conclusion

In this study, an ANN model for daily forecasting of solar radiation time series was implemented. The daily forecasting of solar radiation can contribute to the management and exploitation of solar energy. This model is implemented based on reanalyzed data available over a significant period of time and covering the entire globe with a regular grid. The use of reanalyzed data in the training of ANN models may be less effective than the direct use of measurement data. However, the latter's unavailability in space and time makes the development of such a model impossible, especially in coastal and maritime areas experiencing a total lack of radiation measurements in Algeria and in several regions of the world. The automatic selection of the optimal architecture for the ANN model based on the input data is also a distinctive characteristic of the implemented model. The solar radiation data from Oran used in the ANN model training and neural network performance tests were collected for a period of 39 y. The performance of the model is evaluated using two error parameters: MAE and RMSE. It was found that the predicted values are in harmony with the measured values of NASA for the ANN model, and the results obtained indicated that the artificial neural network model can estimate with good accuracy the daily solar radiation in the reference station located in Oran (Algeria). However, we noted that during some sudden decrease in solar radiation, the ANN model slightly overestimated the daily radiation. The RMSE obtained is 3.248 MJ/(m^2 d) for the ANN model, which reflects a good accuracy compared to the previously implemented model [54,58,59]. The technique of development and implementation of the developed ANN model allows the user of solar renewable energy, professional or amateur, to develop ANN models with a good accuracy that corresponds to their area of interest. This technique, based on reanalyzed data, allows implementation of ANN models on marine and coastal areas even in the absence of measurement data and can be of great use for solar energies farms and for seawater desalination plants that use solar energies. Accurate daily prediction can allow ensuring optimal daily management and exploitation of solar energies.

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