A Review on Solar Radiation Assessment and Forecasting In Algeria
(Part 2: Solar Radiation Forecasting)

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Abstract: Solar radiation forecasting is an important component in many areas related to either the production or exploitation of renewable energies. This field has attracted the attention of many Algerian researchers due to its important solar potential especially in the southern desert areas. In a comprehensive review of the works in this domain, we propose a comprehensive review of the different models and studies for predicting solar radiation in Algeria. Various techniques have been proposed including artificial stochastic models and intelligence.

Keywords: Solar radiation, forecasting models, forward prediction models.

1. Stochastic models.
2. Artificial neural networks.
3. Fuzzy logic.
4. Combined Models.
5. Support vector machines.
6. Wavelet networks.
7. Wavelet-Gaussian process regression model.

A time series is a sequence of numerical values representing the evolution of a specific quantity over time. Such sequences of random variables can be expressed mathematically in order to analyze their behavior, generally to understand their past evolution and to predict its future behavior. A mathematical transposition most often uses concepts of probabilities and statistic. An overview on solar time series modeling in Algeria indicated that several approaches have been considered such as auto-recursive, neural network, Fuzzy logic and vector support machine modeling.

1. STOCHASTIC MODELS

For radiation solar modeling, several stochastic models can be found such as autoregressive (AR), Auto Regressive Integrated Moving Average (ARIMA), seasonal Auto Regressive Integrated Moving Average (SARIMA) and Markov Chain modeling.

Much of the current literature pays particular attention to the stochastic modeling of solar radiation. In this context, it can founded the work of Maafi et al. who have used first-order two-states (bad&fine weather) Markov chains to model daily sunshine duration and GSR data recorded in United Kingdom, Kuwait and four Algerian sites (Algiers, Batna, Oran and Setif) between 8 and 21 years [1]. Obtained results are presented in table 1, where the number of days for which the PV system cannot feed the load is determined via conditions on K-km. In [2], the authors found that a first-order two-state Markov chain fits the daily GSR data recorded between 1972 and 1982 in Algiers. In [3], after statistical comparison between the isolation fractions of the same data and a sequence of threshold values, they found that an overall threshold equal to 0.43 was the best value to fit Algiers’s solar radiation by a first-order two-state Markov process.

In another investigation, Gairaa et al. have indicated that prediction of GSR via ARMA model yields an RMSE 15.5% greater than that obtained by nonlinear autoregressive (NAR) ANN model for the site of Ghardaia. Fig. 1 presents a Scatter plot for ARMA (2,0) model for the site of Ghardaia [4].

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Table 1: Calculated \( (K-k_m) \) and observed \( (D) \) numbers of days of shortage of a PV system \( (k_m = 5 \text{ days}) \) [01].

| Month     | \( \Delta H \) (kWh/m\(^2\).month) | \( P_{50} \) | \( \sigma \) | \( K \) (day) | \( K-k_m \) (day) | \( D \) (day) |
|-----------|-----------------------------------|-------------|------------|--------------|-----------------|-------------|
| January   | 13.6                              | 0.72        | 3.03       | 8.5          | 3.5             | 4.2         |
| February  | 14.5                              | 0.67        | 2.50       | 7.6          | 2.6             | 2.6         |
| March     | 15.7                              | 0.60        | 1.94       | 6.7          | 1.7             | 0.5         |
| April     | 15.4                              | 0.45        | 1.22       | 5.3          | 0.3             | 0.4         |
| May       | 13.0                              | 0.40        | 1.05       | 4.5          | ---             | 0.1         |
| June      | 6.30                              | 0.31        | 0.81       | 2.6          | ---             | ---         |
| July      | 3.2                               | 0.06        | 0.26       | 0.1          | ---             | ---         |
| August    | 2.4                               | 0.10        | 0.35       | 1.0          | ---             | ---         |
| Septembre | 7.2                               | 0.31        | 0.81       | 2.8          | ---             | ---         |
| October   | 13.8                              | 0.58        | 1.78       | 6.0          | 1.0             | 0.2         |
| November  | 13.2                              | 0.74        | 3.28       | 8.9          | 3.9             | 1.8         |
| December  | 9.7                               | 0.78        | 3.90       | 9.4          | 4.4             | 4.5         |

The same results have been obtained by Benmouiza et al. who demonstrated that, for Ghardaïa site HGSR data, an ARMA model is less efficient than NAR model and the hybrid model ARMA-NAR with an nRMSE of 0.3241, 0.2634 and 0.2034, respectively [05].

2. ARTIFICIAL NEURAL NETWORKS (ANN)

ANNs are widely used in solar radiation forecasting because they provide promising solutions using only few available parameters as inputs. There are different ANN architectures such as Multilayer Perceptron, Radial Basis Function network and Recurrent Neural Network, etc. Table 3 presents a survey of some bibliographical references using ANN for solar radiation prediction. From a general overview on ANN modeling of solar radiation in Algeria, a reader observes easily that there is a large volume of published studies in this field. Such phenomenon is attributed to the availability of easy-handle software available in abundance through the network and does not require advance knowledge of ANN theory and technology.

As mentioned above ANN have been considered in several researches in Algeria such as the work in [6] where Dahmani et al. have used ANN with 10 meteorological inputs to estimate hourly and 5-min solar radiation at Bouzaréah (Algiers). For the hourly data estimation, the 10-input model gave an nRMSE of 13.33% (Fig. 2). However, without sunshine duration, the nRMSE of the 5-input model was 28.27%. In [7], the authors reviewed the use of ANN in solar radiation estimation and they highlighted the advantages of using ANN in prediction and estimation of solar radiation at different scales of time.
Laidi et al. used a back propagation ANN to predict solar radiation on tilted surfaces using 8 parameters. Data around the year of 2004 of 13 Algerian stations have been used for training and testing while data of one station was used in the interpolation of the ANN. The configuration 5 inputs, 35 hidden layers, and 1 output has given the best accuracy with an RMSE of 5.75 Wh/m² [8]. In [9], the authors used an ANN to predict daily HGSR using data measured at the University of Bilia. The optimized network is obtained with six inputs, six hidden layers and one output; the MAE was less than 20%. In [10], an optimized ANN model has been used to estimate GSR on inclined plane based on HGSR. Data recorded at Bouzaréah has been used to train and validate this model. An MAPE of 0.48% was reached. Then, they extrapolated the model to data measured during 2011 in Bilia. In [11], the authors used ANN to predict daily HGSR. Three geographical parameters: Altitude, latitude, longitude, and three meteorological parameters: air temperature, humidity and wind speed, were the input. Two third of 14745 data measured at the University of Bilia have been used for ANN's training and the rest for its validation. A correlation coefficient of about 81.6% has been obtained.

One study by Guermoui et al. examined five multilayer feed-forward ANN models, by combining three meteorological inputs, to predict the daily GSR. Six hundred samples of daily data measured between 2005 and 2008 at Ghardaïa have been used in training and one hundred for validation. Similarly, to the results of Dahmani, the authors found out that the presence of sunshine duration as an input gave results that are more accurate. A lower nRMSE of 6.12% has been obtained for the model based on sunshine duration and mean air temperature [12]. Fig. 3 presents the MLP model based on sunshine duration and mean air temperature output prediction.

Similarly, and always for the site of Ghardaïa, Rabehi et al. proposed a simple model based on RBF-ANN to predict daily GSR using data recorded from 01/01/2012 to 28/10/2014 in Ghardaïa. The first two years data has been used for training and those of 2014 have been used for validation. An RMSE of 0.014 was obtained [13]. Fig. 4 presents the Error of the training process versus the number of iterations and a comparison between the measured and predicted GSR [13].

![Graph of normalized solar radiation values against days](image1)

![Graph of predicted vs. observed radiation](image2)

**Fig. 3** MLP model based on sunshine duration and mean air temperature output prediction [12].
In another work, solar data recorded in Ghardaïa in 2007 has been considered to validate the estimation of the global, direct and diffuse solar. In the work, Rezrazi et al. used a MLP network optimization methodology used to predict solar components on normal plane and GSR on 30° inclined plane at the same time. It has been found that the best architecture gave a total RMSE of 14.06% as indicated in Table 2 [14].

At Boumerdes university, Miloudi et al. proposed two types of ANN (MLP and RBF) to estimate GSR and PV I(V) curve. In this work, around 700 solar radiation data recorded every 15-min during 2012 at Boumerdes site has been used. The correlation coefficient obtained for MLP and RBF ANNs was 0.997 and 0.998, respectively as indicated in Fig. 5 [15].

Table 2 Error performance and architecture of the 10 best networks on predicting solar radiation [14].

| Architecture | Diffuse (90°) | Direct | Global (90°) | Global (30°) | Total MAPE (%) | MAPE (%) | MBE (%) | RMSE (%) |
|--------------|--------------|--------|--------------|--------------|----------------|----------|----------|----------|
| 4-30-30-4    | 2.78         | 0.62   | 0.37         | 0.91         | 1.17           | 0.32     | 0.05     | 20.27    |
| 4-28-30-4    | 2.87         | 0.61   | 0.37         | 0.91         | 1.18           | 0.35     | 0.02     | 21.84    |
| 4-29-30-4    | **2.86**     | 0.61   | **0.57**     | 0.92         | **1.19**       | 0.40     | **0.07** | **22.59** |
| 4-30-29-4    | 2.90         | 0.61   | 0.37         | 0.96         | 1.20           | 0.45     | **0.05** | 23.28    |
| 4-25-30-4    | 2.92         | 0.61   | 0.40         | 0.93         | 1.21           | 0.47     | **0.08** | 23.16    |
| 4-28-28-4    | 2.91         | 0.61   | 0.36         | 1.00         | 1.22           | 0.47     | 0.02     | 23.92    |
| 4-29-28-4    | 3.02         | 0.64   | 0.37         | 0.89         | 1.23           | 0.28     | 0.05     | 23.60    |
| 4-29-25-4    | 3.07         | 0.59   | 0.38         | 0.93         | 1.24           | 0.28     | 0.10     | 23.16    |
| 4-27-30-4    | 2.96         | 0.68   | 0.38         | 0.95         | 1.24           | 0.28     | 0.10     | 23.16    |
| 4-27-29-4    | 3.02         | 0.66   | 0.37         | 0.95         | 1.25           | 0.28     | 0.10     | 23.16    |

Fig. 4 Error of the training process versus the number of iterations. Measured and predicted GSR [13].
In an investigation into ANN modelling, SaadSaoud et al. proposed the prediction of daily solar irradiation in Tamanrasset via a quaternion ANN. The input parameters contain the combination of two meteorological parameters (air temperature and relative humidity, air temperature and sunshine duration or relative humidity and sunshine duration). They stated that the second combination gave a better nRMSE of 4.01% [16]. In [17], the authors used complex-valued wavelet ANN to predict daily GSR of 6 Maghreb capitals. The two strategies, multi-input single output (MISO) and multi-input multi-output (MIMO) were used. Concerning Algiers, for the first strategy, the configuration (7 inputs, 30 hidden layers) gave the best nRMSE of about 26.96%. For the second strategy, regarding the forecast of 5 days of each month, the configuration (25 inputs, 100 hidden layers) and for the 15-day forecast of each month, the configuration (15 inputs, 100 hidden layers, 15 outputs) gave the best nRMSE of 0.18 and 1.36, respectively. In [18], the authors proceeded similarly using complex-valued ANN. Satellite data have been used to validate this model (Fig. 6). In [19], the authors used the complex-valued ANN to predict daily and hourly solar radiation. They have studied four structures (three of MISO and one of MIMO). Data measured over during 2007 and 2008 in Tamanrasset, are used. They stated that MIMO method gives better results than MISO method. The authors mentioned also that only temperature is required for daily forecasting (nRMSE = 18.9%) and only previous daily solar radiation is needed for 24-hour ahead forecasting and 14 inputs are required for one hour ahead forecasting (nRMSE = 28%).

Asradj et al. have compared four linear regression models with an ANN-based model to estimate the GSR. A database of more than 26000 measurements of solar radiation and five other meteorological parameters recorded every 8-min at Bejaia site has been used. They found that the ANN model gave the best results, the RMSE was only 0.015 [20]. Fig. 7 illustrates a scatter plot of measured (Output) and predicted (Target) using NN model.
In a study, which set out to determine to estimate the coefficients of six new empirical models and to train a Bayesian neural network (BNN), Yacef et al. used daily GSR with maximum and minimum air temperatures measured during the year 2006. Data from summer and winter of 2007 have been used to test the models, while data from February to July 2012 have been used to examine their generalization possibility. It was found that the precision of the proposed models was better than the simple models for the site of Ghardaïa[21].

To predict daily HGSR, Assas et al. examined a five ANN based on meteorological data sets recorded Djelfa. In this work, several combinations of six variables have been investigated. It has been found that including relative humidity has an effective role in solar radiation prediction (RMSE of 0.1273 including humidity and 0.1323 without humidity) [22]. Fig. 8 shows a comparison between predicted and measured data for three ANN architectures.

Fig. 6 Measured and predicted daily GSR for 15 days in the city Algiers [18].

Fig. 7 Scatter plots of measured (Output) and predicted (Target) using NN model [20].
Fig. 8 Predicted and measured daily GSR on testing data using three ANN models [22].
Hasni et al. used ANN to estimate hourly HGSR at Bechar. The ANN models used five inputs (month, day, hour, air temperature and relative humidity). Data measured between 02 February and 31 May 2011 have been used in training, those of June 2011 have been used for validation. An RMSE of 2.997 was obtained [23].

In his major study, Mellit et al. introduced an Evolving Polynomial ANN to predict GSR, air temperature, relative humidity and wind speed. Data recorded during five years in Algiers have been used in this study. As results, it has been found that the obtained that correlation coefficient for GSR prediction was 0.9821. hence, the proposed model provides more accurate results than the wavelet network and ANFIS [24]. In [25], the authors designed and implemented an ANN based model in FPGA hardware to predict daily GSR. Mean average data of temperature, sunshine duration and solar radiation have been used as inputs. Daily data of 9-years, of a south Algerian location, have been used to train the model and those of 1-year to its validation (Fig. 9). Then, the accuracy of the proposed model in the system prediction has been proved by a coefficient of determination of 0.98. In [26], an ANFIS model was used to predict mean monthly clearness indexes $K_T$ and daily GSR in isolated sites. It was formed using a multi-layer perceptron based on fuzzy logic. The inputs were only geographical coordinates—latitude, longitude and altitude—of four Algerian sites, while the outputs are 12 $K_T$ values. The results gave an RMSE between 0.0215 and 0.0235. A comparison of these results with an ANN model was presented. The obtained data has been used to size a PV system. In [27], another ANFIS system was used to predict GSR from daily mean sunshine duration and air temperature. Sunshine duration data, ambient temperature and GSR recorded between 1981 and 1990 in Algiers have been used with 365 solar radiation data used to test the model. An MRE less than 1% has been obtained. In [28], the authors used an ANFIS to predict monthly clearness index using only latitude, longitude, and altitude of sites. Then, sequences of daily solar radiation were generated using Matrices Transition Markov. Monthly measured data of four sites chosen among database of 60 Algerian sites have been used to test and validate the model. The proposed model gave better results compared to three other ANNs (MLP, RBF and RNN). The obtained results have been used in PV systems sizing. In [29], an RBF-ANN has been used to predict daily GSR from sunshine duration and air temperature. Data of a typical reference year from data recorded in Algiers between 1980 and 2000 has been used. 300 samples have been used for network’s training and 65 for its validation. A correlation coefficient of about 0.989 has been obtained.

Fig. 9 Simulation results based on VHDL for prediction of daily GSR data from sunshine duration and mean temperature [25].
Table 3  Survey of some bibliographical references using ANN for solar radiation prediction.

| Ref | Site       | Time step | Output  | Input  | Model   | Statistical Indicator |
|-----|------------|-----------|---------|--------|---------|-----------------------|
|     |            |           |         |        |         | nRMSE | RMSE | MAPE | R^2 |
| [8] | Bouzaréah  | Hourly    | HGSR    | 10     | MLP     | 13.33% | 53.22Wh/m^2 | ---  | 0.981 |
| [08]| Tindouf    | Hourly    | HGSR    | 10     | MLP     | 18.65% | 6.115Wh/m^2 | ---  | 0.965 |
| [10]| Bouzaréah  | ---       | HGSR    | 13     | ---     | 53.22% | 5.750Wh/m^2 | ---  | 0.998 |
| [04]| Ghardaïa  | Daily     | HGSR    | 02     | NAR     | 11.3%  | 666.18Wh/m^2 | ---  | 0.828 |
| [14]| Ghardaïa  | 5-min     | DNI     | 04     | MLP     | 09.22% | 0.27%  | 0.62% | 0.972 |
|     |            |           | NDiff   | 04     | MLP     | 20.27% | 2.78%  | 0.975 |
|     |            |           | NGSR    | 04     | MLP     | 07.03% | 0.37%  | 0.992 |
|     |            |           | IGSR    | 04     | MLP     | 19.73% | 0.91%  | 0.992 |
| [23]| Bechar     | Hourly    | HGSR    | 05     | ---     | 0.17%  | 0.17%  | 0.999 |
| [29]| Algiers    | Daily     | HGSR    | 02     | RBF     | ---    | ---    | 0.998 |
| [12]| Ghardaïa  | Daily     | HGSR    | 02     | MLP     | 06.12% | 1.28MJ/m^2 | ---  | 0.962 |
| [13]| Ghardaïa  | Daily     | HGSR    | 04     | RBF     | 0.014  | ---    | ---   |
| [22]| Djelfa     | Daily     | HGSR    | 07     | MLP     | 0.1169 | ---    | ---   |

HGSR, IGSR, NGSR are global solar radiation on horizontal, inclined and normal plane. NDiff is diffuse solar radiation on normal plane. MLP, RBF, NAR are multilayer perceptron, radial basis function and nonlinear autoregressive ANN architectures.

3. FUZZY LOGIC

Fuzzy Logic is used in a variety of applications including solar radiation forecasting. In fact, FL can resolve the problem of finding an approximate relationship between different inputs (meteorological, astronomical…) and solar radiation data. L.A. Zadeh introduced fuzzy sets theory, where each element belongs partially to a set rather than a full membership. Instead of using physical variables, linguistic variables are used and real numbers between Boolean elements 0 and 1 are accepted [30-32].

SaadSaoud et al. have proposed the fuzzy modeling technique for GSR short-term forecasting (24h ahead). MIMO models have been used with daily GSR and air temperature measured in Tamanrasset. Data of 2007 and 2008 have been used for modeling and those of 2009 for validation. They have found that the use of both inputs (solar radiation and temperature) slightly improves the case with only one input (solar radiation) as indicated in table 4[33].

Table 4  Results of using the fuzzy modeling technique with one and two meteorological inputs

| Number of clusters “c” | MAE (%) | nRMSE (%) | R^2 (%) |
|------------------------|---------|-----------|---------|
| 3                      | 3.476   | 33.18     | 93.79   |
| 5                      | 3.491   | 33.33     | 93.73   |
| 7                      | 3.466   | 33.19     | 93.79   |
| 11                     | 3.480   | 33.28     | 93.75   |
| 15                     | 3.499   | 33.38     | 93.72   |
| 20                     | 3.522   | 33.76     | 93.57   |
| 50                     | 3.755   | 36.28     | 92.57   |
| 3                      | 3.154   | 31.85     | 94.28   |
| 5                      | 3.138   | 32.04     | 94.21   |
| 7                      | 3.119   | 31.84     | 94.28   |
| 11                     | 3.145   | 31.98     | 94.23   |
| 15                     | 3.184   | 32.41     | 94.07   |
| 20                     | 3.240   | 32.92     | 93.88   |
| 50                     | 3.568   | 37.08     | 92.24   |
In an analysis carried by Drif et al., a fuzzy logic applied has been applied to estimate daily GSR at Bouzaréah using sunshine duration. Seven triangular fuzzy subsets have been used for fuzzification where the center of attraction method has been adopted for defuzzification[34].

4. COMBINED MODELS

Combined or hybrid models couple different approaches with the aim to take the advantage of each model and improve the overall prediction accuracy. The combined models are simple, powerful and outperform the individual models. Hybrid approaches include linear models, nonlinear models and both linear and nonlinear models [35-37]. In Algeria, a number of studies have examined the prediction of solar radiation via hybrid models among Benmouiza et al. who have introduced a hybrid model based on autoregressive moving average and non-linear autoregressive neural network to predict HGSR on a small-scale. Solar radiation data recorded in Ghardaïa and Oran have been used. As results, it has been found that ARMA model is suitable for linear behavior while NAR network is more suitable for non-linear behavior. It has been found also that the hybrid model is limited in case of bad weather [38]. In [39], the authors proposed also a model that combines k-means algorithm and non-linear autoregressive ANNs (fig. 10). The application of this model to data from Oran site yielded an nRMSE of 19.85%.

![Fig. 10 Measured and forecasted HGSR by hybrid model for the site of Oran. (a) hourly scale from 1 November to the 30 November of 2010, (b) 30-s scale of 9 February 2005 [39].](image)
In Similar work, Gairaa et al. combined Box-Jenkins model (ARMA) and ANN to predict daily GSR. Measurements recorded between 2012 and 2013 at Bouzareah and Ghardaïa have been used to test this method. The combined model shows a remarkable improvement over ANN and ARMA models considered alone, with an nRMSE of 0.298 and 0.119 for these two sites, respectively [35]. Table 5 and fig. 11, present comparison between measured and estimated values by three models.

In another study by Mellit et al., a hybrid model based on ANN and a Markov transition matrix (MTM) has been used to predict daily GSR using minimum inputs (latitude, longitude and altitude). The ANN is trained to generate monthly solar radiation data and thus the monthly clearness indexes that are used to generate daily clearness indexes using MTM library as indicated in fig. 13. Daily GSR data collected between 1991 and 2000 from 60 meteorological stations, have been used, 56 have been used for training and 4 for testing the neural network. An RMSE not exceeding 8% was obtained [40].

Table 5 Comparison between measured and estimated values by three models [35].

| Site     | Approach | RMSE(Wh/m²) | nRMSE | MBE(Wh/m²) | nMBE | MPE(%) | R²  |
|----------|----------|-------------|-------|------------|------|--------|-----|
| Bouzareah| ARMA     | 1553        | 0.361 | -60.514    | -0.0141 | 28.611 | 0.716 |
|          | ANN      | 1334        | 0.310 | -82.459    | -0.0192 | 24.062 | 0.802 |
|          | Combined | 1286        | 0.298 | -48.591    | -0.0113 | 23.408 | 0.820 |
| Ghardaïa | ARMA     | 813.33      | 0.141 | -7.493     | -0.0013 | 5.626  | 0.882 |
|          | ANN      | 726.65      | 0.126 | -29.364    | -0.0051 | 4.150  | 0.907 |
|          | Combined | 701.18      | 0.119 | -31.458    | -0.0054 | 4.092  | 0.914 |
5. SUPPORT VECTOR MACHINES

The support vector machines (SVM) model introduced by V. Vapnik has been used in various applications including solar radiation prediction and classification. In fact, the SVM model is successful in solving nonlinear regression problems. It is one of the high-performance machine learning tools since it can maximize the generalization ability of the prediction and minimize the prediction error. Also, it could be an alternative technique for training RBF and MLP classifiers [41,42].

For the site of Ghardaïa, Belaid et al. have applied SVM model to predict daily and monthly HGSR. They used 42 combinations of six parameters. The introduction of different measured temperatures ($T_{\text{max}}$, $T_{\text{min}}$, $T_{\text{mean}}$ and $T_{\text{diff}}$), calculated maximum sunshine duration and calculated extraterrestrial solar radiation improved the predictions of hourly data. Whereas, for monthly data, the monthly mean daily of $T_{\text{min}}$ and extraterrestrial solar radiation gave better predictions compared to literature [43]. Fig. 14 presents a comparison between measured and predicted monthly GSR using SVM and MLP models while table 6 shows the Performance results of four selected SVM models using four inputs [43].

![Fig. 14 Measured and predicted monthly GSR using SVM and MLP models: (a) Training and (b) Prediction [43].](image)

Table 6  Performance results of four selected SVM models using four inputs [43].

| Model | Inputs | RMSE (Mj/m$^2$) | nRMSE (%) | MAPE (%) | MBE (Mj/m$^2$) | R   |
|-------|--------|-----------------|-----------|----------|----------------|-----|
| 1     | $T_{\text{max}}$, $T_{\text{min}}$, $T_{\text{mean}}$, $S_0$ | Train 2.727 | 12.740 | 10.181 | 0.105 | 0.900 |
|       |        | Predict 2.798 | 13.266 | 10.503 | -0.207 | 0.894 |
| 2     | $T_{\text{diff}}$, $T_{\text{min}}$, $T_{\text{mean}}$, $S_0$ | Train 2.746 | 12.829 | 10.293 | 0.115 | 0.900 |
|       |        | Predict 2.777 | 13.163 | 10.403 | -0.232 | 0.896 |
| 3     | $T_{\text{max}}$, $T_{\text{min}}$, $T_{\text{mean}}$, $H_0$ | Train 2.727 | 12.742 | 10.137 | 0.101 | 0.901 |
|       |        | Predict 2.779 | 13.172 | 10.458 | -0.221 | 0.896 |
| 4     | $T_{\text{diff}}$, $T_{\text{min}}$, $T_{\text{mean}}$, $H_0$ | Train 2.755 | 12.875 | 10.058 | 0.069 | 0.898 |
|       |        | Predict 2.807 | 13.305 | 10.440 | -0.267 | 0.894 |

6. WAVELET NETWORKS

In [77], SaadSaoud et al. proposed a fully complex valued wavelet network (FCWN) to predict hourly and daily GSR. Wavelet networks combine wavelet decomposition and ANN. The comparison of the results with measurements from Tamanrasset gave an nRMSE of 0.1575 as indicated in table 7 [44]. Fig. 15 presents forecasts of Wavelet models for 4 time scales.
Table 7 Results of FCWN and other forecasting techniques [44].

| Forecasting technique                  | No. of parameters | MAE(%) | nRMSE (%) | $R^2$ (%) |
|----------------------------------------|-------------------|--------|-----------|-----------|
| Real valued neural network (RVNN)      | 551               | 9.71   | 17.61     | 44.62     |
| Complex wavelet network (CWN)          | 331               | 18.91  | 24.69     | 97.09     |
| Complex valued neural network (CVNN)   | 301               | 9.44   | 16.57     | 97.30     |
| Fully complex valued wavelet network (FCWN) | 255            | 8.08   | 15.75     | 97.63     |

Fig. 15 Measured and forecasted solar irradiation with different time scales ahead (a) 24 h, (b) 1 h, (c) 5 days, (d) 15 days [44].

Mellit et al. also applied the wavelet networks to predict daily GSR using 20 year data (1981 to 2001) in Algiers (fig. 16). Data of the 19 first years have been used in training while only those of 2001 have been used in testing. As results, an MAPE less than 6% was obtained. They stated that this model can be used to supplement missing radiation data of meteorological databases [45].

7. WAVELET-GAUSSIAN PROCESS REGRESSION MODEL.

Recently, the Gaussian process regression (GPR) algorithm has been used successfully in remote sensing and Earth sciences. In [46, 47], a wavelet-coupled Gaussian process regression (W–GPR)
model has been developed to predict the daily solar radiation received on a horizontal surface in Ghardaia (Algeria). As a result, it has been demonstrated the effectiveness of the new hybrid W–GPR model compared with the classical GPR model in terms of root mean square error (RMSE), relative root mean square error (rRMSE), mean absolute error (MAE). Fig. 17 presents a comparison between GPR and wavelet coupled GPR models [46].

Fig. 16 Measured and predicted GSR by wavelet-network (structure 5 × 12 × 1 training used 19 years of data) [45].

Fig. 17 The spread of prediction error Pe (MJ/m²day) for the W–GPR model compared with the GPR model[46]

CONCLUSION

A review of solar radiation forecasting in Algeria since 1987 has been carried out in the current study. The strategic geographical location of Algeria in the center of the world and the solar belt, as well as the growing global trend of renewable energy increases the opportunities of this country to invest and even export the surplus energy, especially to Europe.

Through this study, it was noted that a wide range of prediction models based on artificial and artificial intelligence were used. As for stochastic modeling such as ARMA, ARIMA and Gaussian regression, a few studies were found. However, it has been found that most of the prediction models are based on an artificial network. There are some studies
where support vector machines and hybrid models have been used.

It was also noted that the daily solar radiation is the most studied due to its ease of dealing with it as it is a continuous function unlike the hourly solar radiation whose night hours represent a great obstacle especially for stochastic models.

Finally, it should be noted that, and for the same data set of Ghardaia region, different stochastic models were adopted such as ARMA and ARIMA, which constitutes a blatant contradiction that requires re-verification.

References

[1] Maafi A, ADANE AEH. Analysis of the Performances of the First-Order Two-State Markov Model Using Solar Radiation Properties. Renew Energy 1998;13:175–93. doi:10.1016/S0960-1481(97)00094-3.

[2] Maafi A, Adane AEH. A two-state Markovian model of global irradiation suitable for photovoltaic conversion. Sol Wind Technol 1989;6:247–52. doi:10.1016/0741-983X(89)90076-3.

[3] Maafi A, Adane AEH, Ouabdesselam A. Ajustement des Données d’Insolation d’Alger par un Modèle Markovien du Premier Ordre. Rev Phys Appliquée 1987;22:425–30. doi:10.1051/rphysap:0198700220604250 0.

[4] Gairaa K, Chellali F, Benkaciali S, Messlem Y, Abdallah K. Daily Global Solar Radiation Forecasting over a Desert Area Using NAR Neural Networks Comparison with Conventional Methods. 4th Int. Conf. Renew. Energy Res. Appl., IEEE; 2015. p. 567–71. doi:10.1109/ICRERA.2015.7418477.

[5] Benmouiza K, Cheknane A. Small-scale solar radiation forecasting using ARMA and nonlinear autoregressive neural network models. Theor Appl Climatol 2015. doi:10.1007/s00704-015-1469-z.

[6] Dahmani K, Dizene R, Notton G, Paoli C, Voyant C, Nivet ML. Estimation of 5-min time-step data of tilted solar global irradiation using ANN (Artificial Neural Network) model. Energy 2014;70:374–81. doi:10.1016/j.energy.2014.04.011.

[7] Dahmani K, Notton G, Dizene R, Paoli C. Etat de l’art sur les réseaux de neurones artificiels appliqués à l’estimation du rayonnement solaire. Rev Des Energies Renouvelables 2012;15:687–702.

[8] Laidi M, Hanini S, Rezrazi A, Yaiche MR, El Hadj AA, Chellali F. Supervised Artificial Neural Network-Based Method for Conversion of Solar Radiation Data (Case Study: Algeria). Theor Appl Climatol 2016:1–13. doi:10.1007/s00704-015-1720-7.

[9] Laidi M, Hanini S, Cheggaga N, Nadjemi O. Predicting global solar radiation for North Algeria. Int. Conf. Renew. Energies Power Qual. ICREPQ’14, 2014.

[10] Laidi M, Hanini S. Prediction and extrapolation of global solar radiation on tilted surfaces from horizontal ones using an artificial neural network. 3rd Int. Symp. Environ. Friendly Energies Appl. EFEA2014, IEEE; 2014, p. 1–6. doi:10.1109/EFEA.2014.7059998.

[11] Laidi M, Cheggaga N, Hanini S. Artificial neural network estimation of 5-min solar global radiation values using air temperature, relative humidity and wind speed in the region of Baida (Algeria), first Int. Conf. Nanoelectron. Commun. Renew. Energy, 2013, p. 449–55.

[12] Guermoui M, Rabehi A, Benkaciali S, Djafer D. Daily global solar radiation modelling using multi-layer perceptron neural networks in semi-arid region. Leonardo Electron J Pract Technol 2016:35–46.

[13] Rabehi A, Guermoui M, Djafer D, Zaiani M. Radial Basis Function Neural Networks Model to Estimate Global Solar Radiation in Semi-Arid Area. Leonardo Electron J Pract Technol 2015:177–84.

[14] Rezrazi A, Hanini S, Laidi M. An optimisation methodology of artificial neural network models for predicting solar radiation: a case study. Theor Appl Climatol 2015:123:769–83. doi:10.1007/s00704-015-1398-x.

[15] Miloudi L, Acheli D. Prediction Global Solar Radiation and Modeling Photovoltaic Module Based on Artificial Neural Networks. 3rd Int. Conf. Control. Eng. Inf. Technol. CEIT 2015, IEEE; 2015, p. 1–6. doi:10.1109/CEIT.2015.7233111.

[16] SaadSaoud L, Rahmoune F, Tourtchine V, Baddari K. Quaternion neural network to forecast the daily solar irradiation. 3rd
[17] SaadSaoud L, Rahmoune F, Tourchine V, Baddari K. Complex-Valued Wavelet Neural Network Prediction of the Daily Global Solar Irradiation of the Great Maghreb Region. Prog. Clean Energy, vol. 1, 2015, p. 321–39. doi:10.1007/978-3-319-16709-1.

[18] SaadSaoud L, Rahmoune F, Tourchine V, Baddari K. Prediction of the Daily Global Solar Irradiation of the Great Maghreb Region Using the Complex-Valued Neural Networks. Rev Des Energies Renouvelables 2014;17:173–85. doi:10.1007/978-3-319-16709-1_23.

[19] SaadSaoud L, Rahmoune F, Tourchine V, Baddari K. Complex-Valued Forecasting of the Global Solar Irradiation. J Renew Sustain Energy 2013;5:1–22. doi:10.1063/1.4818618.

[20] Asradj Z, Alkama R, Demir S, Tekin A. MLP/Levenberg-Marquardt for Prediction Solar Radiation: A Case Study Bejaia City. In: Oral A., Bahsi Oral Z., Ozer M, editors. 2nd Int. Congr.Energy Effic.Energy Relat.Mater., Cham: Springer International Publishing; 2015, p. 53–60. doi:10.1007/978-3-319-16901-9.

[21] Yacef R, Mellit A, Belaid S, Şen Z. New combined models for estimating daily global solar radiation from measured air temperature in semi-arid climates: Application in Ghardaia, Algeria. Energy Convers Manag 2014;79:606–15. doi:10.1016/j.enconman.2013.12.057.

[22] Assas O, Bouzgou H, Fetah S, Salmi M, Boursas A. Use of the Artificial Neural Network and Meteorological Data for Predicting Daily Global Solar Radiation in Djelfa, Algeria. IntConf Compos Mater Renew Energy Appl ICCMREA 2014 2014. doi:10.1109/ICCMREA.2014.6843807.

[23] Hasni A, Sehli A, Draoui B, Bassou A, Amieur B. Estimating global solar radiation using artificial neural network and climate data in the south-western region of Algeria. Energy Procedia 2012;18:531–7.

[24] Mellit A, Drif M. EPNN-Based Prediction of Meteorological Data for Renewable Energy Systems. Rev Des Energies Renouvelables 2010;13:25–47.

[25] Mellit A, Shaari S, Mekki H, Khorissi N. FPGA-based Artificial Neural Network for Prediction of Solar Radiation Data from Sunshine Duration and Air Temperature. Int. Conf. Comput. Technol. Electr. Electron. Eng., IEEE; 2008. p. 118–23. doi:10.1109/SIBIRCON.2008.4602597.

[26] Mellit A, Kalogirou SA, Shaari S, Salhi H, Hadj Arab A. Methodology for Predicting Sequences of Mean Monthly Clearness Index and Daily Solar Radiation Data in Remote Areas: Application for Sizing a Stand-Alone PV System. Renew Energy 2008;33:1570–90. doi:10.1016/j.renene.2007.08.006.

[27] Mellit A, Hadj Arab A, Khorissi N, Salhi H. An ANFIS-Based Forecasting for Solar Radiation Data from Sunshine Duration and Ambient Temperature. IEEE Power Eng. Soc. Gen. Meet., 2007, p. 1–6. doi:10.1109/PES.2007.386131.

[28] Mellit A, Hadj Arab A, Shaari S. An ANFIS-Based Prediction for Monthly Clearness Index and Daily Solar Radiation: Application for Sizing of a Stand-Alone Photovoltaic System. J PhysSci 2007;18:15–35.

[29] Mellit A, Benghanem M, Bendekhiss M. Artificial Neural Network Model for Prediction Solar Radiation Data: Application for Sizing Stand-alone Photovoltaic Power System. Power Eng. Soc. Gen. Meet., IEEE; 2005. doi:10.1109/PES.2005.1489526.

[30] Mellit A. Artificial Intelligence technique for modelling and forecasting of solar radiation data: a review. Int J Intell Soft Comput 2008;1:52–76.

[31] Mellit A, Kalogirou SA. Artificial intelligence techniques for photovoltaic applications: A review. Prog Energy Combust Sci 2008;34:574–632. doi:10.1016/j.pecs.2008.01.001.

[32] Badescu V. Modeling Solar Radiation at the Earth’s Surface. 2008. doi:10.1007/978-1-4471-4649-0_5.

[33] SaadSaoud L, Rahmoune F, Tourchine V, Baddari K, Saoud LS, Rahmoune F, et al. Short-Term Forecasting of the Global Solar Irradiation Using the Fuzzy Modeling Technique: Case Study of Tamanrasset City, Algeria. Prog. Clean Energy, vol. 1, 2015, p. 281–9. doi:10.1007/978-3-319-16709-1.

[34] Drif M, Chikh M. Estimation de l’irradiation Solaire par la Logique Floue.
[35] Gairaa K, Khellaf A, Messlem Y, Chellali F. Estimation of the daily global solar radiation based on Box-Jenkins and ANN models: A combined approach. Renew Sustain Energy Rev 2016;57:238–49. doi:10.1016/j.rser.2015.12.111.

[36] Shamshirband S, Mohammadi K, Khorasanizadeh H, Yee PL, Lee M, Petković D, et al. Estimating the diffuse solar radiation using a coupled support vector machine–wavelet transform model. Renew Sustain Energy Rev 2016;56:428–35. doi:10.1016/j.rser.2015.11.055.

[37] Diagne M, David M, Lauret P, Boland J, Schmutz N. Review of solar irradiance forecasting methods and a proposition for small-scale insular grids. Renew Sustain Energy Rev 2013;27:65–76. doi:10.1016/j.rser.2013.06.042.

[38] ONM. Catalogue des produits et services de Météo Algérie 2015. http://www.meteo.dz/catalogueonligne.php (accessed April 11, 2017).

[39] Benmouiza K, Cheknane A. Forecasting hourly global solar radiation using hybrid k-means and nonlinear autoregressive neural network models. Energy Convers Manag 2013;79:561–9. doi:10.1016/j.enconman.2013.07.003.

[40] Mellit A, Benghanem M, Hadj Arab A, Guessoum A. A simplified Model for Generating Sequences of Global Solar Radiation Data for Isolated Sites: Using Artificial Neural Network and a Library of Markov Transition Matrices Approach. Sol Energy 2005;79:469–82. doi:10.1016/j.solener.2004.12.006.

[41] Mellit A, MassiPavan A, Benghanem M. Least squares support vector machine for short-term prediction of meteorological time series. Theor Appl Climatol 2013;111:297–307. doi:10.1007/s00704-012-0661-7.

[42] Jang HS, Member S, Bae KY, Member S. Solar Power Prediction Based on Satellite Images and Support Vector Machine 2016;7:1255–63. doi:10.1109/TSTE.2016.2535466.

[43] Belaid S, Mellit A. Prediction of Daily and Mean Monthly Global Solar Radiation Using Support Vector Machine in an Arid Climate. Energy Convers Manag 2016;118:105–18. doi:10.1016/j.enconman.2016.03.082.

[44] SaadSaoud L, Rahmoune F, Tourchine V, Baddari K. Fully Complex Valued Wavelet Network for Forecasting the Global Solar Irradiation. Neural Process Lett 2016.doi:10.1007/s11063-016-9537-7.

[45] Mellit A, Benghanem M, Kalogirou SA. An adaptive wavelet-network model for forecasting daily total solar-radiation. Appl Energy 2006;83:705–22. doi:10.1016/j.apenergy.2005.06.003.