A Review on Solar Radiation Assessment and Forecasting In Algeria

(Part 2: Solar Radiation Forecasting)

Nourdine KABOUCHE [(1,3)], Farouk CHELLALI [(1,2)*] and Abdelmadjid RECIOUI[(1)]
[(1)] Laboratory of Signals and Systems, Institute of electrical and electronic Engineering, University M'hamedBougara of Boumerdes, 35000, Boumerdes, Algeria.
[(2)]Departement of electrical engineering, University of ZianeAchour, Djelfa.
[(3)] Centre de développement des énergies renouvelables, CDER, 16340, Algiers, Alegria.
*Corresponding author F.chellali@mail.univ-djelfa.dz

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. Such 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 Ghardaïa. Fig. 1 presents a Scatter plot for ARMA (2,0) model for the site of Ghardaïa [4].

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

Month	ΔH (kWh/m^2.month)	P_{00}	σ	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

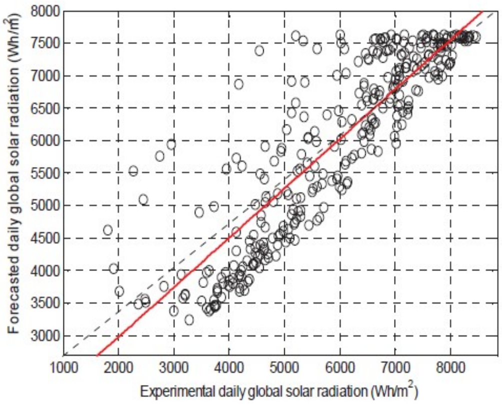

Fig. 1 Scatter plot for ARMA (2,0) model (Ghardaïa) [04].

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.

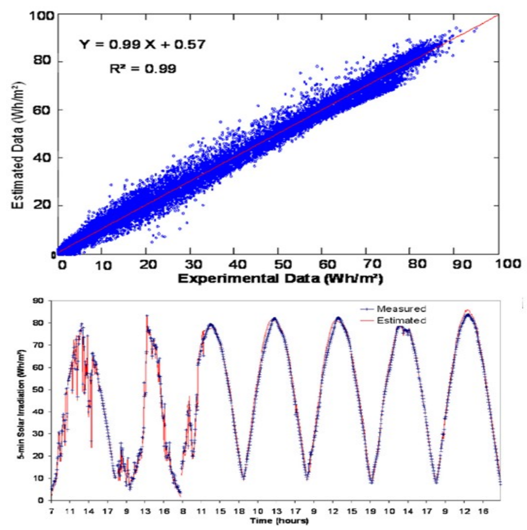

Fig. 2 Measured and 5-min estimated IGSR [06].

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 Blida. 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 Blida. 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 Blida 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 vadidation. 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].

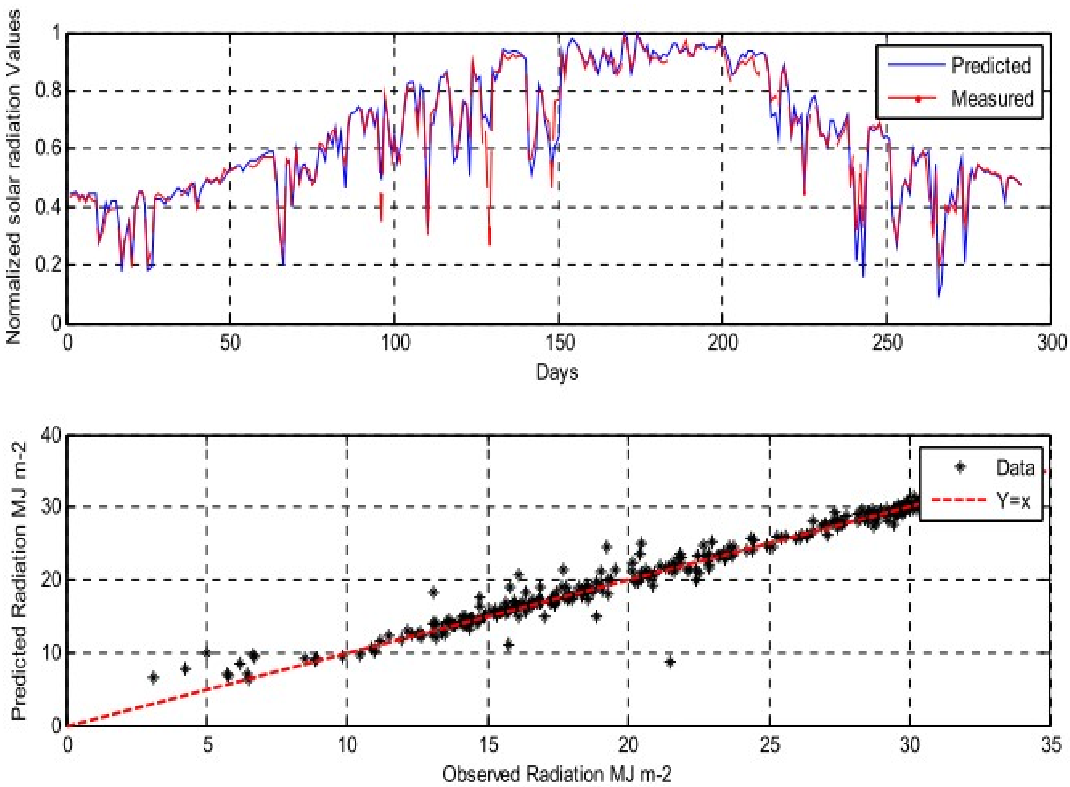

Fig. 3 MLP model based on sunshine duration and mean air temperature output prediction [12].

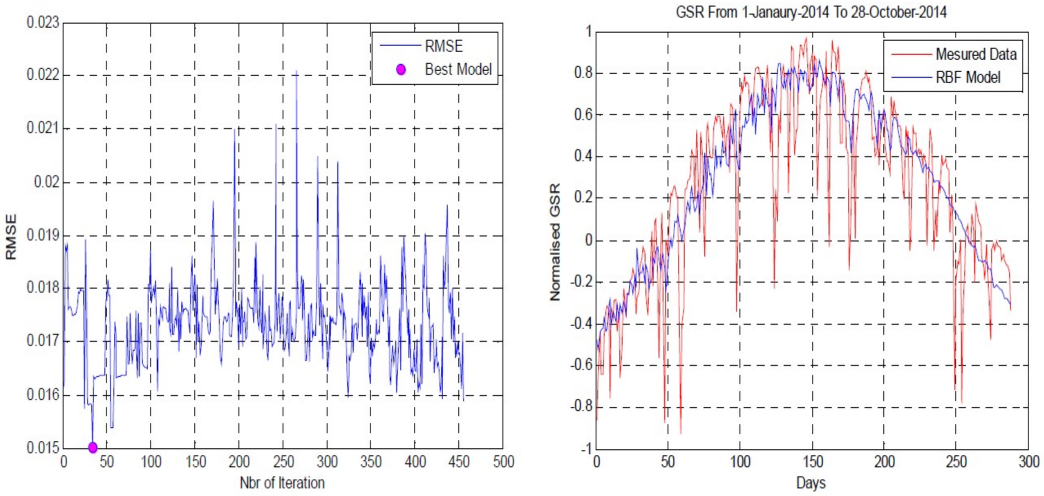

Fig..4 Error of the training process versus the number of iterations. Measured and predicted GSR [13].

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	4-30-30-4	4-28-30-4	4-29-30-4	4-30-29-4	4-25-30-4	4-28-28-4	4-29-28-4	4-29-25-4	4-27-30-4	4-27-29-4
MAPE (%)	Diffuse (90°)	2.78	2.87	**2.86**	2.90	2.92	2.91	3.02	3.07	2.96	3.02
	Direct	0.62	0.61	0.61	**0.57**	0.60	0.61	0.64	0.59	0.68	0.66
	Global (90°)	0.37	**0.34**	0.37	0.37	0.40	0.36	0.37	0.38	0.38	0.37
	Global (30°)	0.91	0.91	0.92	0.96	0.93	1.00	**0.89**	0.93	0.95	0.95
Total MAPE (%)		**1.17**	1.18	1.19	1.20	1.21	1.22	1.23	1.24	1.24	1.25
MBE (%)	Diffuse (90°)	0.32	0.35	0.40	0.55	0.13	0.47	0.17	0.28	0.72	**0.10**
	Direct	0.05	0.02	0.27	0.22	0.05	0.08	0.02	0.07	**0.10**	0.05
	Global (90°)	0.08	**0.02**	0.04	0.09	0.15	0.10	0.05	0.11	0.09	0.46
	Global (30°)	0.05	0.19	0.07	0.29	**0.03**	0.16	0.19	0.20	0.23	0.76
Total MBE (%)		0.12	0.14	0.19	0.28	**0.09**	0.20	0.10	0.16	0.28	0.34
RMSE	Diffuse (90°)	**20.27**	21.84	22.81	22.59	23.28	21.92	20.90	22.48	21.78	26.94
	Direct	**9.22**	9.70	9.81	9.98	10.28	9.60	9.47	9.42	9.93	10.96
	Global (30°)	7.03	7.20	7.11	**6.98**	7.08	7.10	7.00	7.06	7.00	7.40
	Global (90°)	19.73	20.06	19.70	19.95	20.6	20.16	19.76	**19.66**	20.33	21.54
Total RMSE (%)		**14.06**	14.7	14.85	14.87	15.31	14.69	14.28	14.65	14.76	16.71

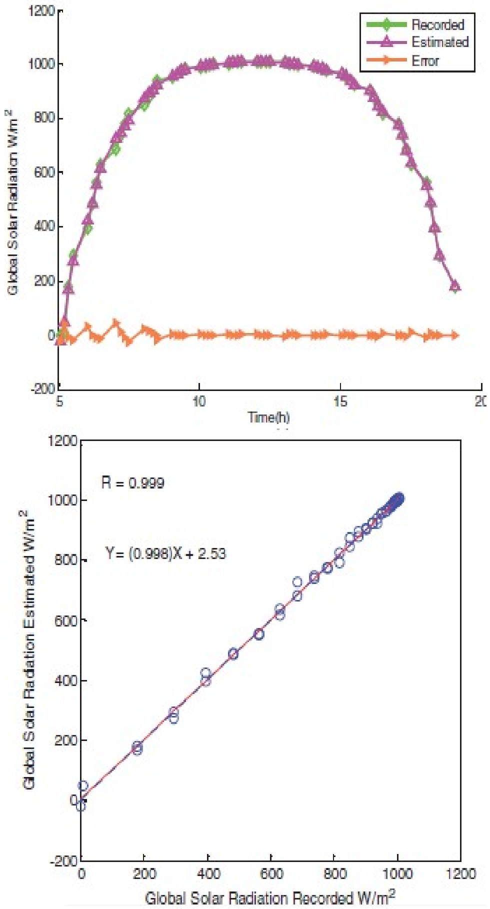

Fig. 5. Regression analysis between recorded and estimated GSR [15].

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 = 26%).

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.

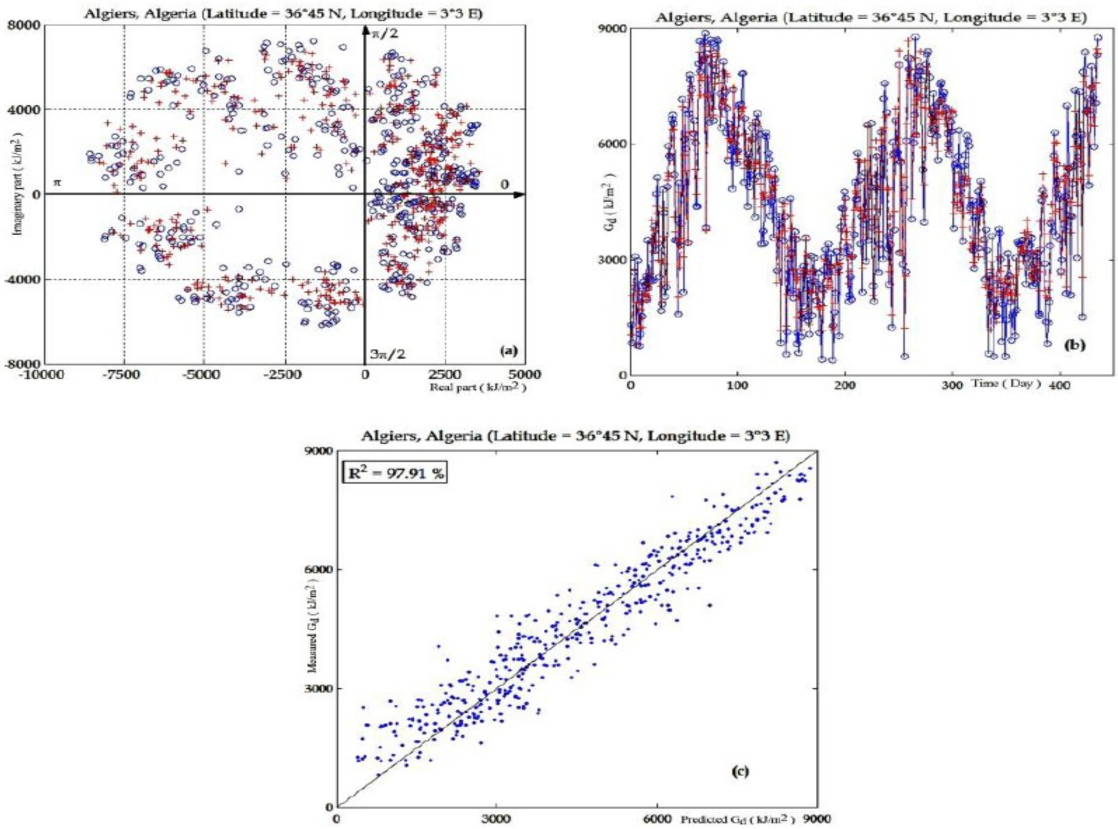

Fig. 6 Measured and predicted daily GSR for 15 days in the city Algiers [18].

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.

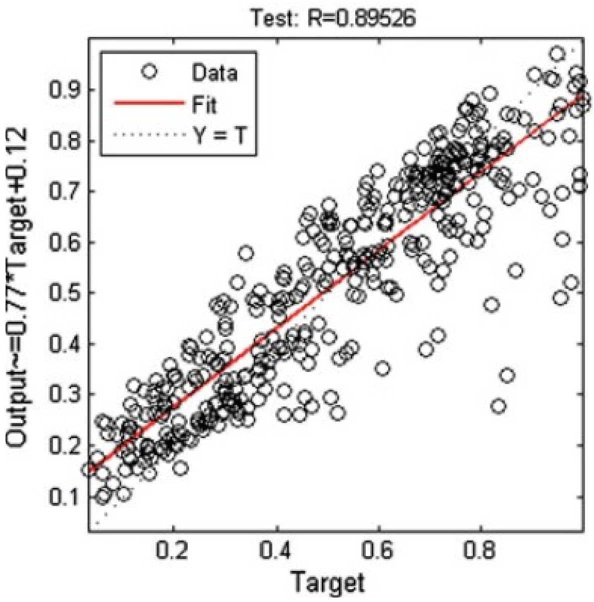

Fig. 7 Scatter plots of measured (Output) and predicted (Target) using NN model [20].

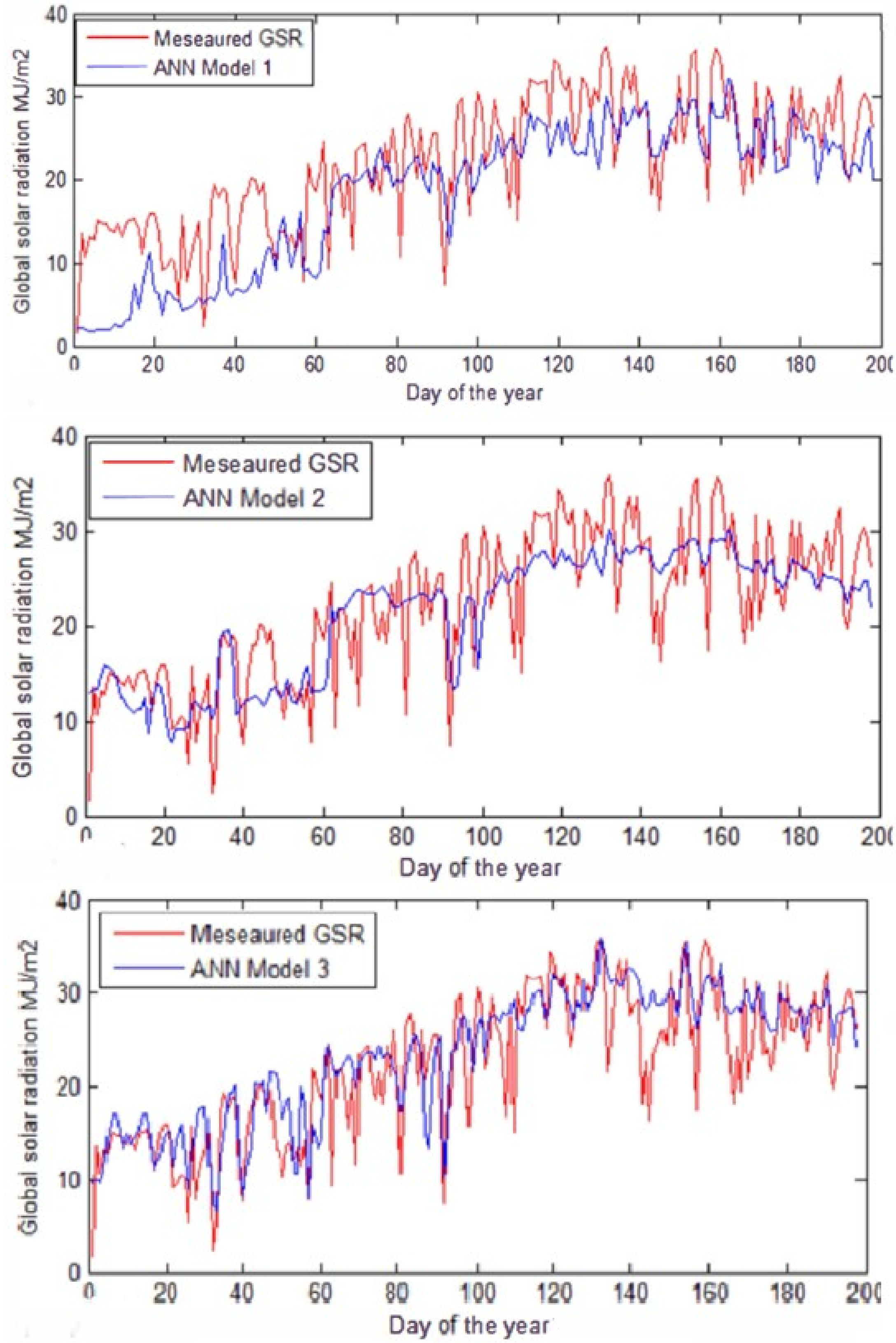

Fig. 8 Predicted and measured daily GSR on testing data using three ANN models [22].

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 i9n 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.

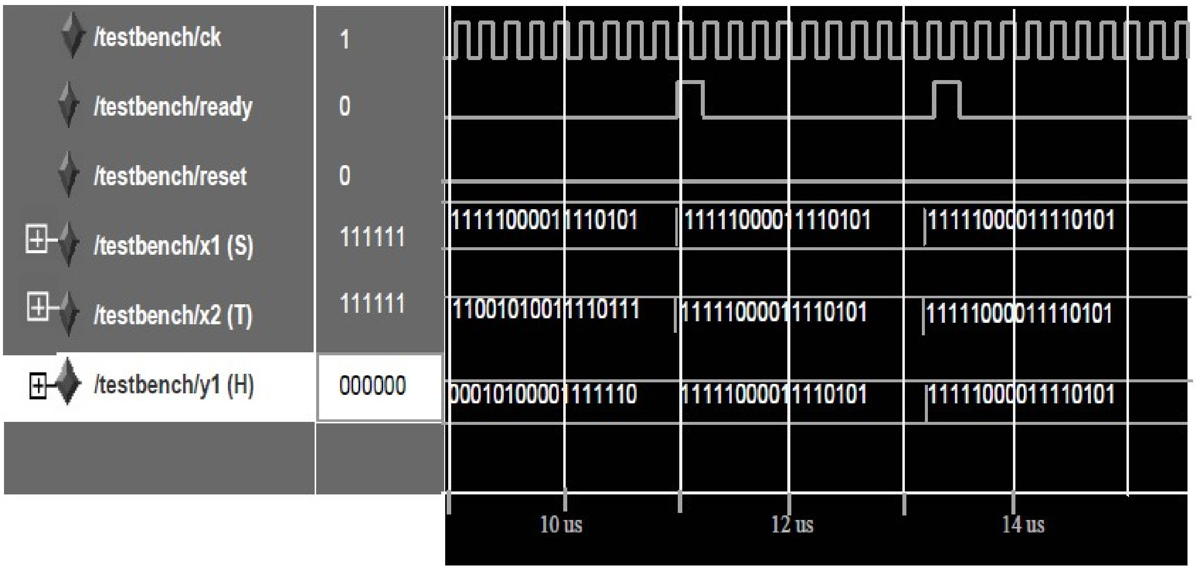

Fig. 9 Simulation results based on VHDL for prediction of daily GSR data from sunshine duration and mean temperature [25].

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]	Bouzaréa	Hourly	HGSR	10	MLP	13.33%	53.22Wh/m^2	---	0.981
		5-min	HGSR	10	MLP	18.65%	6.115Wh/m^2	---	0.965
[08]	Tindouf	Hourly	IGSR	05	MLP	---	5.750Wh/m^2	---	0.998
[10]	Bouzaréa	---	IGSR	13	---	---	---	0.48%	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%	---	0.62%	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	---	---	0.172	---	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 [33].

	Number of clusters "c"	MAE (%)	*nRMSE* (%)	R^2 (%)
$\{\hat{G}_{1h}(i),\hat{G}_{2h}(i),\dots,\hat{G}_{24h}(i)\}=f(G_d(i-1))$	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
$\{\hat{G}_{1h}(i),\hat{G}_{2h}(i),\dots,\hat{G}_{24h}(i)\}=f(G_d(i-1),T_d(i-1))$	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 couples 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%.

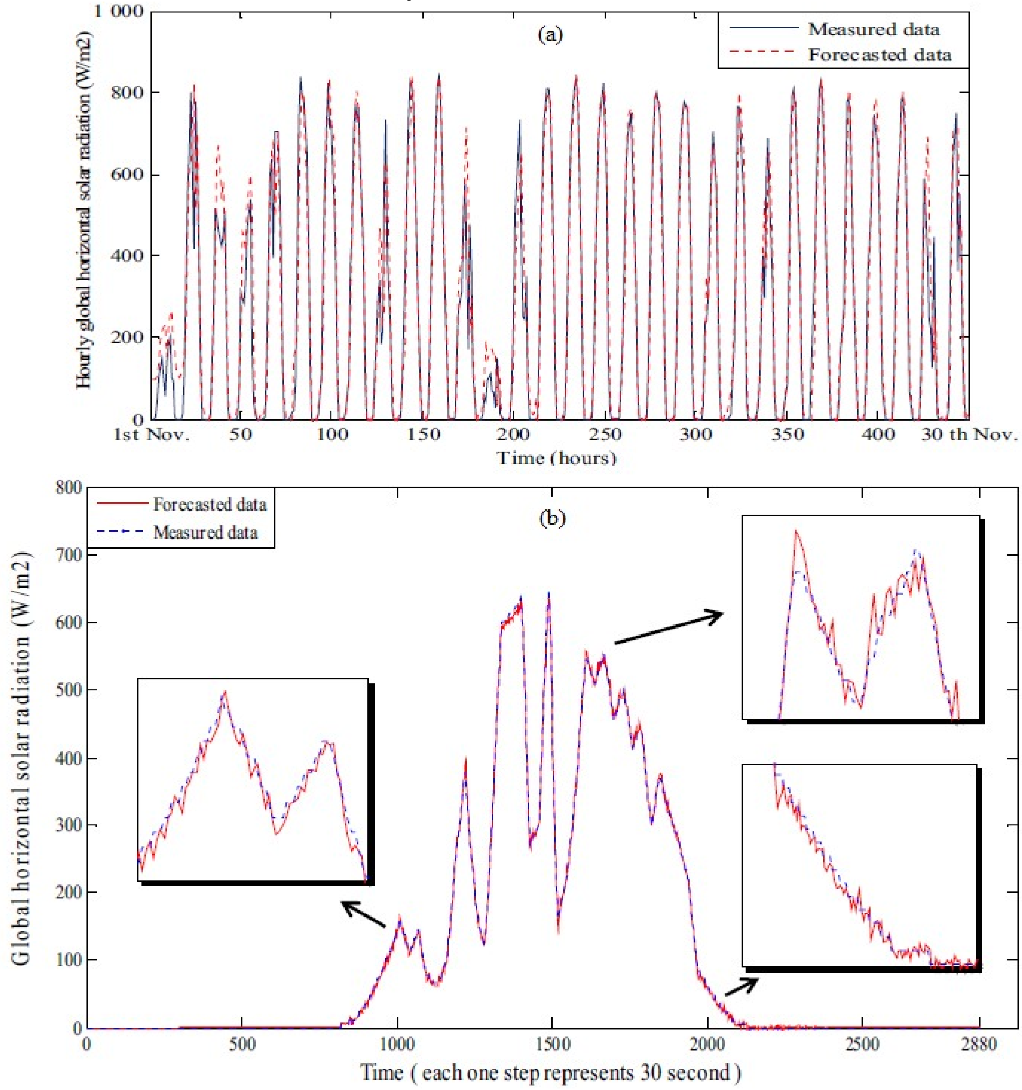

Fig. 10 Measured and forecasted HGSR by hybrid model for the site of Oran, (a) hourly scale from 1 November to the 30 November of 2010, (b) 30-s scale of 9 February 2005 [39].

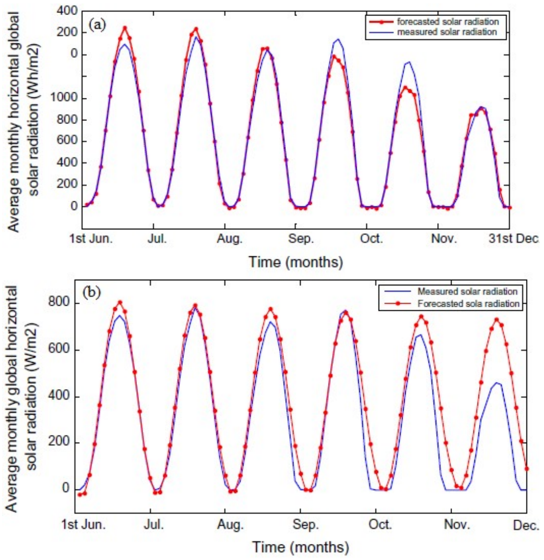

Fig. 11 Measured and forecasted monthly HGSR (from July 1996 to December 1996) by: (a) the proposed model, (b) ARMA model [39].

In Similar work, Gairaa et al. combined Box-Jenkins model (ARMA) and ANN to predict daily GSR. Measurements recorded between 2012 and 2013 at Bouzaréah 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].

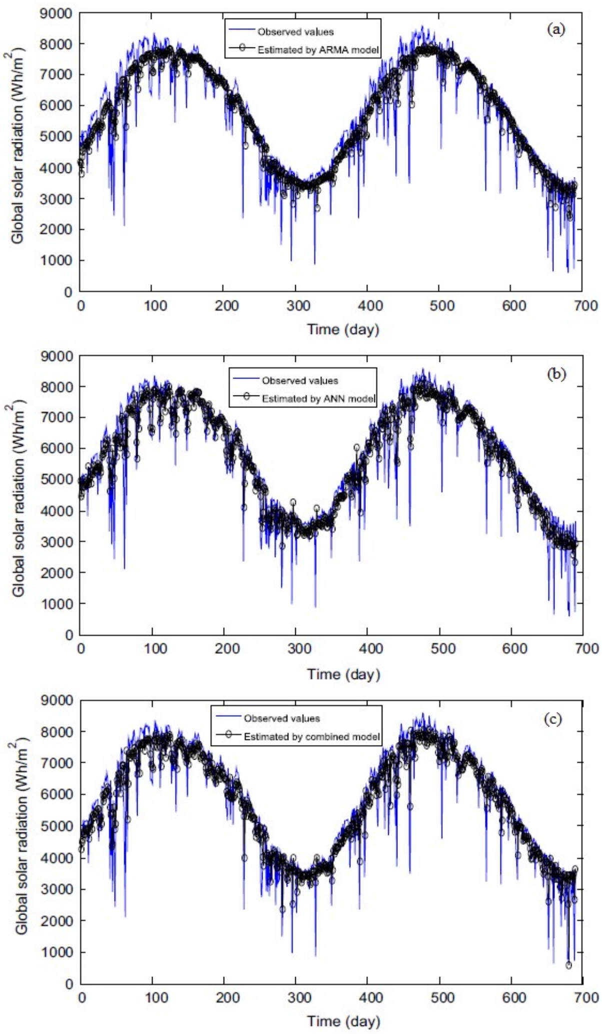

Fig. 12 Measured against estimated daily GSR by (a) ARMA (2,0), (b) NAR and (c) combined models in Ghardaïa[35].

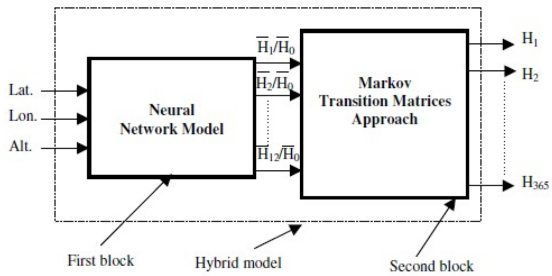

Fig. 13b Block diagram of the hybrid model [40].

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

Site	Approach	RMSE(Wh/m^2)	nRMSE	MBE(Wh/m^2)	nMBE	MPE(%)	R^2
Bouzaréah	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_{max}, T_{min}, T_{mean} and T_{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_{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].

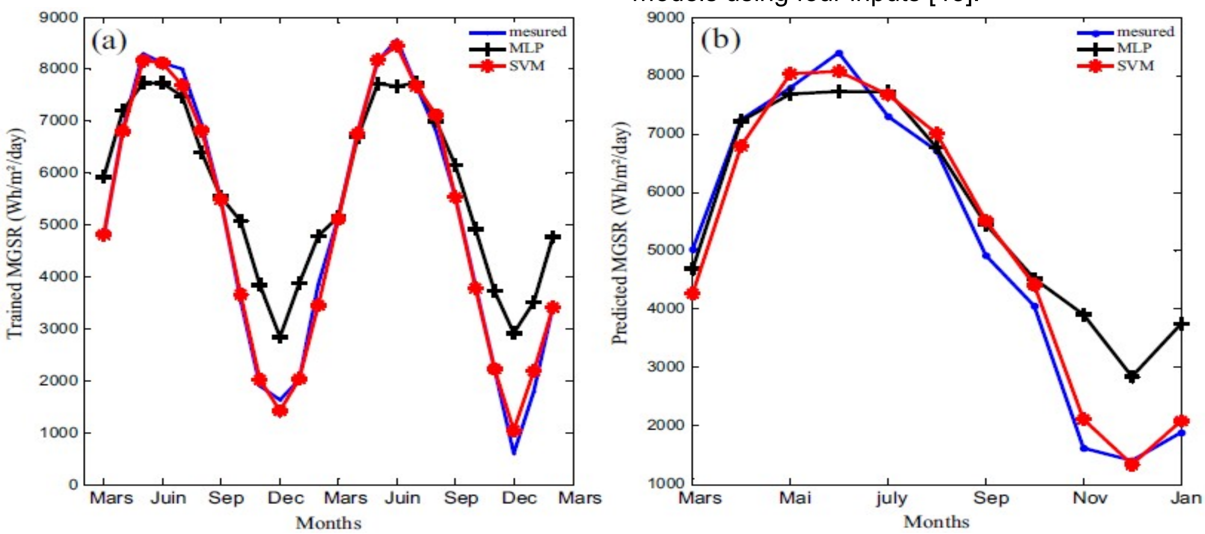

Fig. 14 Measured and predicted monthly GSR using SVM and MLP models: (a) Training and (b) Prediction [43].

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_{max}, T_{min}, T_{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_{diff}, T_{min}, T_{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_{max}, T_{min}, T_{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_{diff}, T_{min}, T_{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

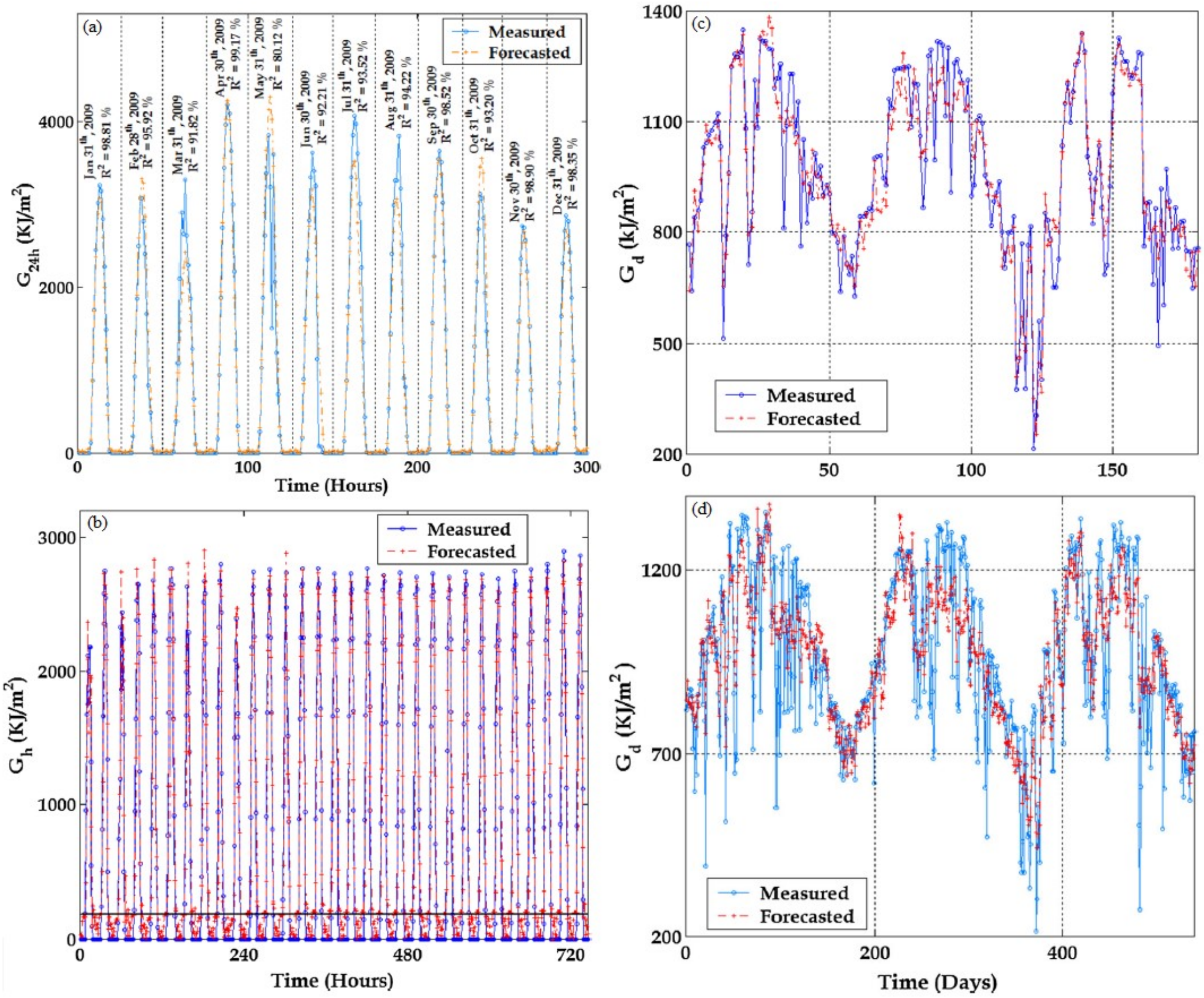

Fig. 15Measured and forecasted solar irradiation with different time scales ahead (a) 24 h, (b) 1 h (c) 5 days (d) 15 days [44].

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 results, 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].

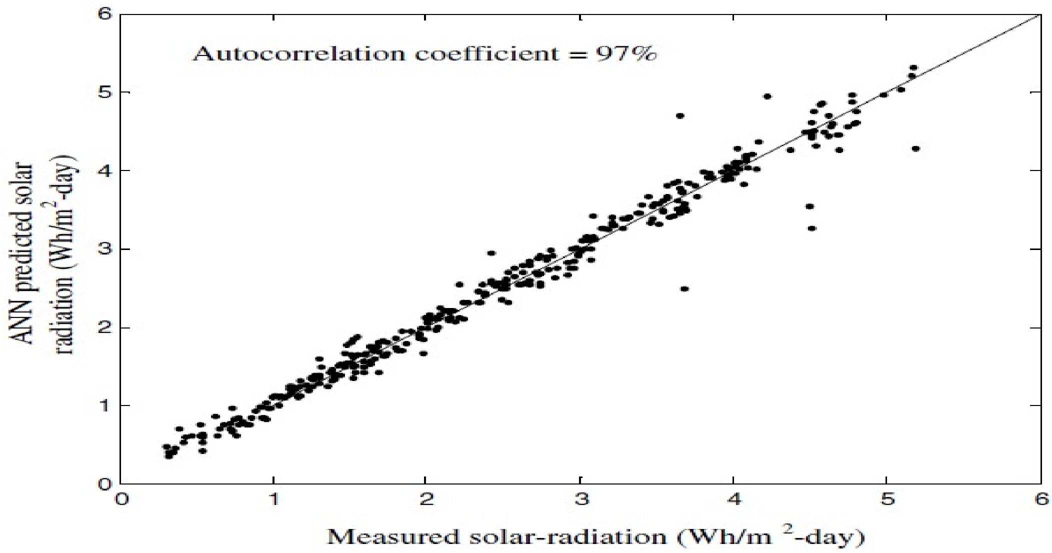

Fig. 16 Measured and predicted GSR by wavelet-network (structure 5_X12_X1 training used 19 years of data) [45].

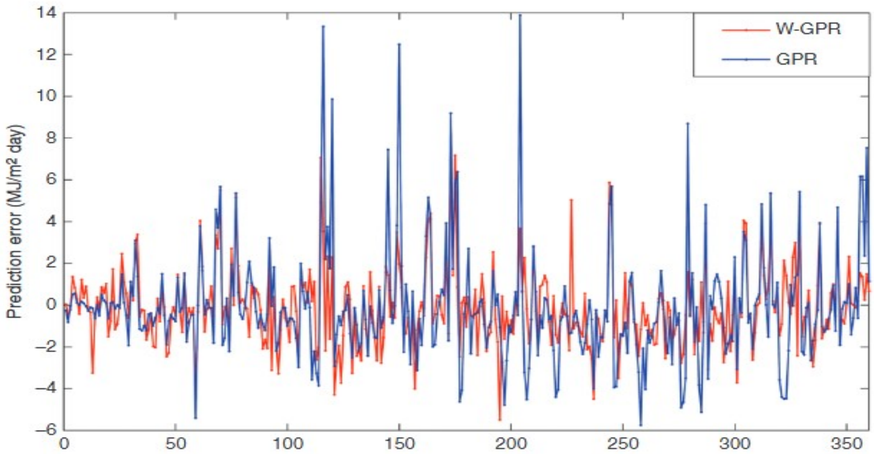

Fig. 17 The spread of prediction error Pe (MJ/m2day) for the W–GPR model compared with the GPR model[46]

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

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