Prediction of the daily global solar Irradiation of the great Maghreb region using the complex-valued neural networks

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(reçu le 30 Octobre 2013 – accepté le 31 Mars 2014)

Résumé - *Dans cet article, la prédiction du rayonnement solaire global quotidien de la région du grand Maghreb en utilisant les réseaux de neurones à valeurs complexes (RNVC) est présentée. Ce papier est une extension de notre travail récent basé sur la prévision à valeur complexe de l'irradiation solaire globale. Les deux stratégies, multi-entrée sortie unique (MESU) et multi-entrées multi-sorties (MEMS) sont envisagées. Les données concernant les capitales du grand Maghreb, qui sont Tripoli (Libye), Tunis (Tunisie), Alger (Algérie), Rabat (Maroc), El Ayoun (Sahara occidental) et Nouakchott (Mauritanie), sont utilisées comme échantillon de chaque pays. Pour tester l'applicabilité et la faisabilité du RNVC pour prédire l'irradiation globale quotidienne dans le cas du grand Maghreb, plusieurs modèles sont présentés. Les résultats obtenus dans ce papier montrent que la technique RNVC est adaptée pour la prédiction de l'irradiation solaire quotidienne de la région du grand Maghreb.*

Abstract - *In this paper, the prediction of the daily global solar irradiation of the great Maghreb's region using the complex-valued neural networks (CVNN) is presented. This paper is an extension of our recent published work which is the complex-valued forecasting of the global solar irradiation. Both multi-input single-output (MISO) and multi-input multi-output (MIMO) strategies are considered. The data of the capitals of the great Maghreb, which are Tripoli (Libya), Tunis (Tunisia), Algiers (Algeria), Rabat (Morocco), El Aaiun (Western Sahara) and Nouakchott (Mauritania), are used like sample from each country. To test the applicability and the feasibility of the CVNN to predict the daily global irradiation for the great Maghreb case, several models are presented. Results obtained throughout this paper show that the CVNN technique is suitable for prediction of the daily solar irradiation of the region of region of the great Maghreb.*

Keywords: Solar irradiation, Complex-valued neural networks, prediction, Great Maghreb.

1. INTRODUCTION

Global solar irradiation is considered as the most important parameter in the design of renewable and solar energy systems, particularly for the sizing of Photovoltaic (PV) systems [1]. This parameter changes from location to another due to the sunlight variation and other meteorological parameters.

In the great Maghreb, where the desert of Sahara occupied a large part, the global solar irradiation could be found in great quantity. This opportunity gives the thermal and the photovoltaic applications great advantages.

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Due to the high nonlinearity of the solar irradiation model and the dependence between this last parameter with other meteorological and geo-astronomical data, many models based on computational techniques dedicated to predict the solar irradiation could be found in literature [2-12], whereas, the neural networks are widely used to forecast solar irradiation with good accuracy [13-19].

Complex-Valued Neural Networks (CVNNs) prove their abilities for the identification of nonlinear systems. They can outperform their real counterparts in many ways [20]. CVNNs give also the possibility of the simultaneous modeling and forecasting [21], where they have been used to forecast the wind's speed and direction simultaneously. The main motivation to use the CVNNs is the faster convergence, reduction in learning parameters and ability to learn two dimension motion of signal in complex-valued neural network [22].

The CVNNs are simply the generalization of the real valued neural networks in the complex valued domain, where all the parameters including weights, biases, inputs and outputs could be complex variables.

In our previous work [19], the complex valued neural networks (CVNN) are proposed to forecast the hourly and the daily solar irradiation where the application is specified to Tamanrasset city (Algeria).

In this paper the same strategies are used for the great Maghreb, which gives more comprehension and shows better the feasibility of CVNN in different locations. On the other hand, it shows which location in the great Maghreb the strategy is more or less suitable.

2. COMPLEX-VALUED NEURAL NETWORKS

The main difference between the Real-Valued Neural Networks (RVNNs), i.e. neural networks, and the Complex-Valued Neural Networks (CVNNs) is coming from the nature of the parameters that exist into the network. By definition real variables are particular case of complex variables.

Consequently, complex-valued neural networks are simply an extension of the real-valued neural networks to the complex plane. Mathematically speaking, if the input vector X_n, the weights ($W^1_{m0}, W^2_{l0}, W^1_{mn}$ and W^2_{lm}) and the nonlinear function f_c in the equations (1) and (2) are real valued the resulting network is RVNN else (i.e. one or all the above parameters is/are complex valued) the resulting network is CVNN [19].

The complex Back-Propagation (BP) algorithm, which is the complex valued version of the real valued back propagation algorithm, is widely used to train the CVNNs [23-24]. The complex-BP algorithm outlined from [23] is used to train the networks.

Let us take the complex valued neural network which has n inputs, m neurons in the hidden layer and l outputs. The l^{th} network's output could be calculated as follows:

$$\hat{y}_l(k) = f_c\left(W^2_{l0} + \sum_m W^2_{lm} \times H_m \right) \tag{1}$$

and the output of each hidden neuron m is given like:

$$H_m = f_c\left(W^1_{m0} + \sum_n W^1_{mn} \times X_n \right) \tag{2}$$

Where: $X_n = \left[y(k-1),\ y(k-2),\ \cdots, y(k-i),\ u(k-1),\ u(k-2),\ \cdots,\ u(k-q) \right]$, which contains $n = i + q$ complex valued input. With n, m, i, l and q are positive integers.

W^1_{m0}, W^2_{l0}, W^1_{mn} and W^2_{lm} are biases and the weights from the input to hidden and from the hidden to the output layers, respectively. $f_c(.)$ is a complex valued activation function.

According to the Liouville's theorem, in which the analytic and bounded functions on entire complex plane are constant, the $f_c(.)$ takes a great attention and several complex activation functions proposed in the literature [24]. In this paper the split sigmoid function is taken and it is given as follows:

$$f_c(z) = \frac{1}{1+e^{-\mathrm{Re}(z)}} + j \times \frac{1}{1+e^{-\mathrm{Im}(z)}} \tag{3}$$

Where: $z = x + j \times y$.

It should be noted that the use of the split sigmoid function rather than the non-split function could avoid the problem of function's singularity, due to the fact that non-split sigmoid function has singular points at every $z = j \times (2n+1)\pi$, $z \in Z$ [24], with $j = \sqrt{-1}$ is the complex number.

The complex-BP algorithm is given as follows:

$$\Delta W^2_{l0} = \eta \times \begin{bmatrix} \mathrm{Re}(e_l(k)) \times \mathrm{Re}(\hat{y}_1(k)) \times (1-\mathrm{Re}(\hat{y}_1(k)) \\ + j \times \mathrm{Im}(e_1(k)) \times \mathrm{Im}(\hat{y}_1(k)) \times (1-\mathrm{Im}(\hat{y}_1(k)) \end{bmatrix} \tag{4}$$

$$\Delta W^2_{lm} = \left[\mathrm{Re}(H_m) - j \times \mathrm{Im}(H_m) \right] \times \Delta W^2_{l0} \tag{5}$$

$$\begin{aligned} \Delta W^2_{l0} = \eta \times [\ & \mathrm{Re}(H_m) \times (1-\mathrm{Re}(H_m)) \times \sum_l (\mathrm{Re}(e_l(k)) \times \mathrm{Re}(\hat{y}_l(k)) \\ & \times (1-\mathrm{Re}(\hat{y}_1(k))) + \mathrm{Re}(\Delta W^2_{lm}) + \mathrm{Im}(e_1(k)) \times \mathrm{Im}(\hat{y}_1(k)) \times (1-\mathrm{Im}(\hat{y}_1(k))) \\ & \times \mathrm{Im}(\Delta W^2_{lm})) - j\, \mathrm{Im}(H_m) \times (1-\mathrm{Im}(H_m)) \\ & \times \sum_l (\mathrm{Re}(e_l(k)) \times \mathrm{Re}(\hat{y}_l(k)) \times (1-\mathrm{Re}(\hat{y}_1(k))) \times \mathrm{Im}(\Delta W^2_{lm}) \\ & - \mathrm{Im}(e_1(k)) \times \mathrm{Im}(\hat{y}_1(k)) \times (1-\mathrm{Im}(\hat{y}_1(k)))\, \mathrm{Im}(\Delta W^2_{lm}))\ ] \end{aligned} \tag{6}$$

$$\Delta W^1_{mn} = \left[\mathrm{Re}(X_n) - j \times \mathrm{Im}(X_n) \right] \times \Delta W^1_{m0} \tag{7}$$

Where $e_l(k)$ is the error between the l^{th} desired output $k_l(k)$ and the l^{th} predicted output $\hat{y}_l(k)$ which is given as follows:

$$e_l(k) = y_l(k) - \hat{y}_l(k) \tag{8}$$

3. DATA PREPARATION

According to the main objective of this study, the capitals of the great Maghreb (Fig. 1) are taken to implement the CVNN technique. The lack of experimental data (or the difficulty to obtain them) of the whole region, requires us to use satellite data. Satellite data (daily solar irradiation, daily air temperature and daily relative humidity) are obtained from the official website of NASA [25] for the following cities:

Tripoli, Libya: Latitude = 32°53 N, Longitude = 13°11 E,

Tunis, Tunisia: Latitude = 36°49 N, Longitude = 10°10 E,

Algiers, Algeria: Latitude = 36°45 N, Longitude = 3°3 E,

Rabat, Morocco: Latitude = 34°1 N, Longitude = 6°50 W,

El Aaiun, Western Sahara: Latitude = 27°8 N, Longitude = 13°13 W,

Nouakchott, Mauritania: Latitude = 18°5, Longitude = 15 ° 59 W.

Fig. 1: The Great Maghreb with its capitals (modified form [26])

To make data useful to the CVNNs, it should be transformed into the complex valued domain. The same procedure has done in [19], will be realized in this work. Therefore, each year's day will be represented by an angle, with one year is assumed to be a circle (2π). In this case, the time index will be integrated into the data itself which produces one input that contains two simultaneous parameters (the meteorological data and the time index). The complex valued temporal index $t_c(d)$ for the daily case is given by the following equation (9) [19]:

$$t_c(d) = e^{(j2\pi d / 365)} \tag{9}$$

where $d = 1, \ldots, 365$, represent the days number, with the first day is the 1st January.

By multiplying the obtained complex valued time index with each meteorological parameter (T_m , H_m , G_m), the complex valued of : the daily air temperature T_d, relative humidity H_d and the daily global solar irradiation G_d could be found, which are given by the following equations:

$$T_d = T_m \times e^{(j2\pi d / 365)} \tag{10}$$

$$H_d = H_m \times e^{(j2\pi d / 365)} \tag{11}$$

$$G_d = G_m \times e^{(j2\pi d / 365)} \tag{12}$$

The values of the meteorological data (T_m, H_m, G_m) represent arithmetic mean values (i.e. average values) during one day (over 24-h).

The satellite data for the six cities (Tripoli, Tunis, Algiers, Rabat, El Aaiun, Nouakchott) are daily air temperature, relative humidity and daily solar irradiation in the duration 01/01/2003 to 06 / 30/2005. Two years (2003 - 2004) are used to train the CVNN and the rest (180 days) for its validation.

To have an idea about the prediction performance of the applied algorithm, the normalized Root Mean Squared Error ($nRMSE$) [13], the coefficient of determination (R^2) and the Mean Absolute Error (MAE) [27] given below are taken like criteria for all examples (its units are in %), where N is the number of samples:

$$nRMSE = \frac{\sqrt{\frac{1}{N} \times \sum_{k=1}^{N} \left| y_k - \hat{y}_k \right|^2}}{\bar{y}} \tag{13}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{N} \left| y_k - \hat{y}_k \right|^2}{\sum_{k=1}^{N} \left| y_k - \bar{y}_k \right|^2} \tag{14}$$

$$MAE = \frac{\sum_{k=1}^{N} \left| y_k - \hat{y}_k \right|}{N} \tag{15}$$

It should be noted that MAE in % is calculated by multiplying the obtained value by 100 and dividing the result by the maximum of the measured data.

4. RESULTS

Since only the satellite values of daily air temperature, daily relative humidity and daily solar irradiation can be downloaded, the prediction of solar irradiation will be based only on these two parameters. These results are presented in **Tables 1**, **2**, **3** and **4** for the case of the daily solar irradiation prediction. It should be mentioned that we use the notation $\langle I \times H \times O \rangle$ in all tables, where I, H and O represent the number of neurons in input layer, the number of neurons in the hidden layer and the number of neurons in the output layer, respectively. According to the values of I, H and O several architectures could be obtained.

It can be seen in **Table 1**, for the all capitals, the temperature alone gives a good estimation results. Better results are obtained using air temperature for the city El Aaiun (MAE = 10.804 %, nRMSE = 19.3 % and R^2 = 94.43 %) compared to the other cities. The results for the city Tunis are the worst (nRMSE= 34.0 % and R^2 = 85.66 %). In the practical case, the first strategy, that uses the air temperature, is the appropriate choice because it has a quality of estimation acceptable and a low price in the conception point of view.

Table 1: Obtained results using CVNN in the case of one meteorological input

Model's structure		Capital	Measure's Criteria		
	< IxHxO>		MAE (%)	nRMSE(%)	R^2 (%)
$\hat{G}_d(k) = f(T_d(k-1))$	< 1x10x1>	Tripoli	14.203	30.6	87.31
		Tunis	13.745	34.0	85.66
		Algiers	14.610	33.5	86.66
		Rabat	13.777	28.0	89.99
		El Aaiun	10.804	19.3	94.43
		Nouakchott	11.042	20.7	93.27
$\hat{G}_d(k) = f(H_d(k-1))$	< 1x10x1>	Tripoli	15.448	31.1	86.80
		Tunis	16.656	38.5	81.69
		Algiers	15.420	33.9	86.30
		Rabat	16.305	32.3	86.71
		El Aaiun	10.847	19.0	94.58
		Nouakchott	24.219	36.8	78.88

In the case of combining the two parameters (**Table 2**), the results are improved. But despite this improvement, the relative humidity can be eliminated due to the fact that the same results could be almost found using the air temperature.

Table 2: Obtained results using CVNN in the case of the two meteorological inputs

Model's structure		Capital	Measure's criteria		
	< IxHxO>		MAE(%)	nRMSE(%)	R^2 (%)
$\hat{G}_d(k) = f(T_d(k-1), H_d(k-1))$	< 2x10x1>	Tripoli	12.460	27.2	89.97
		Tunis	13.084	32.0	87.29
		Algiers	14.278	32.1	87.74
		Rabat	12.426	25.0	92.03
		El Aaiun	9.652	17.9	95.19
		Nouakchott	10.776	20.3	93.54

The same remark could be deduced, which is the good performance given by the CVNN for city El Aaiun (MAE = 9.652%, nRMSE = 17.9% and R2 = 95.19%), with worst quality (but not very bad) is obtained for cities Tunis (MAE = 13.084%, nRMSE = 32% and R^2 = 87.29%) and Algiers (MAE = 14.278%, nRMSE = 32.1% and R^2 = 87.74%).

The case of, 10 neurons in the hidden layer with 12 inputs (temperature, relative humidity and 10 past values of the solar irradiation) in **Table 3**, seems to give good results for all cities. With the best among them are obtained for the towns El Aaiun and Nouakchott.

Table 3: Obtained results using CVNN in the case of the two meteorological inputs and delayed solar irradiation

Model's structure		Capital	Measure's criteria		
	< IxHxO>		MAE(%)	nRMSE (%)	R^2 (%)
$\hat{G}_d(k)=f(T_d(k-1), H_d(k-1), G_d(k-1),\cdots,G_d(k-10))$	<12x10x1> <12x30x1> <12x50x1>	Tripoli	11.674 11.980 13.322	24.8 25.3 27.3	91.73 91.38 89.98
$\hat{G}_d(k)=f(T_d(k-1), H_d(k-1), G_d(k-1),\cdots,G_d(k-10))$	<12x10x1> <12x30x1> <12x50x1>	Tunis	12.828 14.455 18.144	31.2 33.7 40.2	88.16 86.12 80.20
$\hat{G}_d(k)=f(T_d(k-1), H_d(k-1), G_d(k-1),\cdots,G_d(k-10))$	<12x10x1> <12x30x1> <12x50x1>	Algiers	13.556 16.877 21.512	29.5 35.5 44.2	89.69 85.10 76.97
$\hat{G}_d(k)=f(T_d(k-1), H_d(k-1), G_d(k-1),\cdots,G_d(k-10))$	<12x10x1> <12x30x1> <12x50x1>	Rabat	10.606 12.242 13.036	21.7 24.0 25.3	94.07 92.74 91.91
$\hat{G}_d(k)=f(T_d(k-1), H_d(k-1), G_d(k-1),\cdots,G_d(k-10))$	<12x10x1> <12x30x1> <12x50x1>	El Aaiun	8.767 9.789 9.110	16.2 17.5 17.0	96.13 95.47 95.71
$\hat{G}_d(k)=f(T_d(k-1), H_d(k-1), G_d(k-1),\cdots,G_d(k-10))$	<12x10x1> <12x30x1> <12x50x1>	Nouakchott	8.316 8.821 9.569	16.7 17.8 18.8	95.71 95.11 94.58

The results for the MIMO strategy to predict several days ahead at one time are presented in **Table 4**, in which one can see the appropriate quality of prediction. The cities: Tripoli, Tunis and Algiers are chosen as examples for the case of prediction 15 days of each month using the past 15 days of each month(i.e. predict $\hat{G}_{16d}(k+1)$, $\hat{G}_{17d}(k+1)$,…, $\hat{G}_{30d}(k+1)$ using $G_{1d}(k)$, $G_{2d}(k)$,…, $G_{15d}(k)$ of each month).

Results for the above selected cities are shown in Figures (2) to (4), in which the data are represented in both polar and temporal domains and the measured versus predicted outputs as well. We can see the high performance and quality given by the CVNN in the MIMO case, especially for the city of Algiers. In the introduction of other meteorological parameters (**Table 4**), the results are improved in both cases, predict either 15 or 5 days of each month.

Table 4: Obtained results using the CVNN in the MIMO case

Model's structure		Capital	Measure's criteria		
	< I×H×O>		MAE (%)	nRMSE (%)	R^2 (%)
$\{\hat{G}_{26d}(k),\cdots,\hat{G}_{30d}(k)\}= f(G_{1d}(k-1), G_{2d}(k-1),\cdots,G_{25d}(k-1))$	<25×30×5>	Tripoli Tunis Algiers Rabat El Aaiun Nouakchott	0. 130 0. 125 0. 104 0. 229 0. 239 0.206	1.2 1.5 1.2 2.2 1.9 1.8	97.37 97.21 98.11 91.98 91.10 90.39
$\{\hat{G}_{26d}(k),\cdots,\hat{G}_{30d}(k)\}=f(T_d(k-1), H_d(k-1), G_{1d}(k-1), G_{2d}(k-1),\cdots,G_{25d}(k-1))$	<27×30×5>	Tripoli Tunis Algiers Rabat El Aaiun Nouakchott	0. 171 0. 112 0. 154 0. 140 0. 229 0. 149	1.9 1.2 1.8 1.3 1.9 1.1	94.04 98.07 95.50 96.96 90.21 95.99
$\{\hat{G}_{16d}(k),\cdots,\hat{G}_{30d}(k)\}= f(G_{1d}(k-1), G_{2d}(k-1),\cdots,G_{15d}(k-1))$	<15×30×15>	Tripoli Tunis Algiers Rabat El Aaiun Nouakchott	0. 070 0. 114 0. 092 0. 110 0. 133 0. 092	1.4 2.4 1.6 2.0 1.9 1.2	98.79 99.24 97.91 98.73 99.01 98.97
$\{\hat{G}_{16d}(k),\cdots,\hat{G}_{30d}(k)\}=f(T_d(k-1), H_d(k-1), G_{1d}(k-1), G_{2d}(k-1),\cdots,G_{15d}(k-1))$	<17×30×15>	Tripoli Tunis Algiers Rabat El Aaiun Nouakchott	0. 071 0. 099 0.065 0.053 0.080 0.038	1.4 1.9 1.2 0.8 1.1 0.5	98.78 99.04 98.61 98.73 99.20 99.24

In the case of prediction of the five days a head using the past twenty five days of each month (for the other cities), results for the cities: Rabat, El Aaiun, and Nouakchott are shown in Figures 5 to 7. Again, we can see the good prediction qualities given by CVNN, but they are not better than those obtained for other cities.

We can see in **Table 4** that the CVNN gives good results. In 25 × 30 × 5 case, the network is best for Tripoli, Tunis and Algiers. But the network with 15 × 30 × 15 structure gives good results for the six capitals.

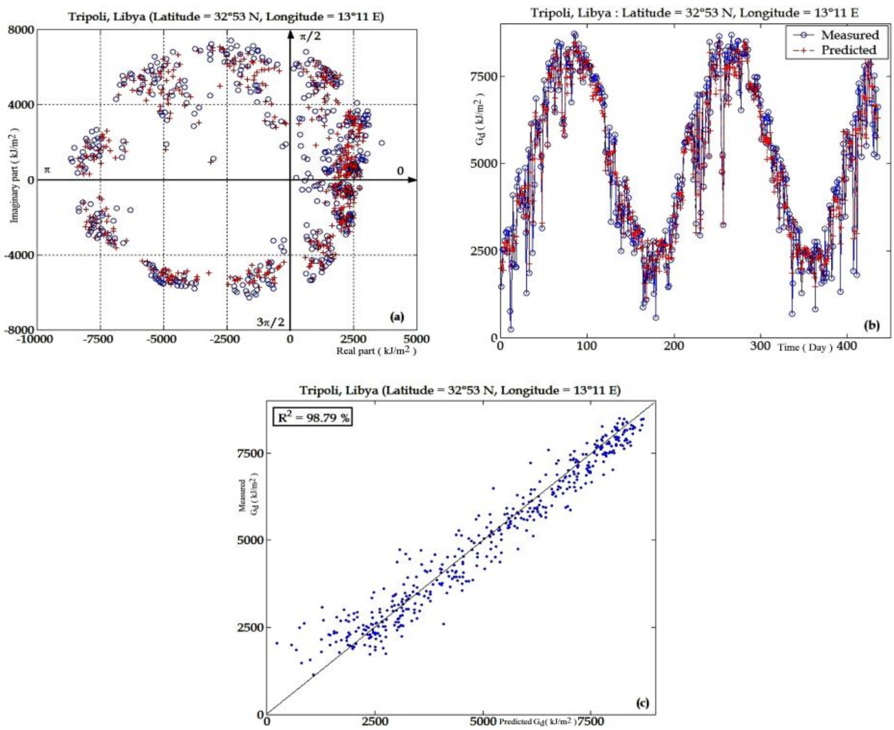
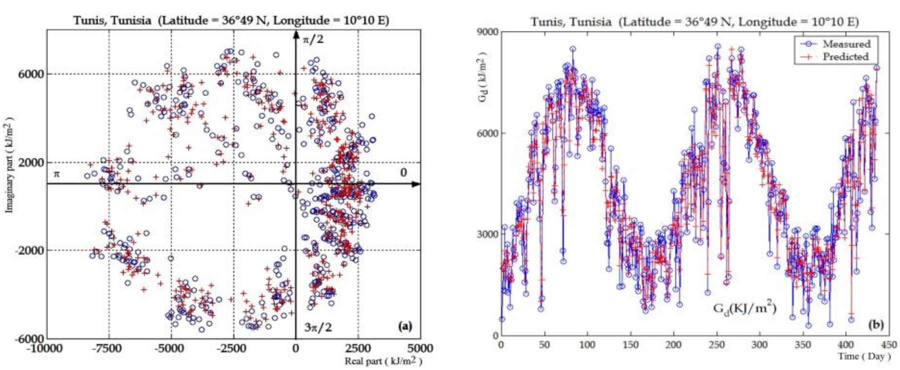


Fig. 2: Measured and predicted daily solar irradiation for 15 days in the city Tripoli (a) in the polar plane, (b) temporal and (c) measured versus predicted



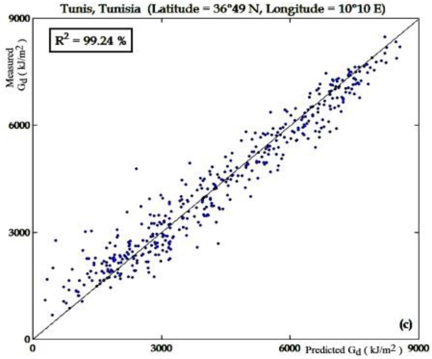


Fig. 3: Measured and predicted daily solar irradiation for 15 days in the city Tunis (a) in the polar plane, (b) temporal and (c) measured versus predicted

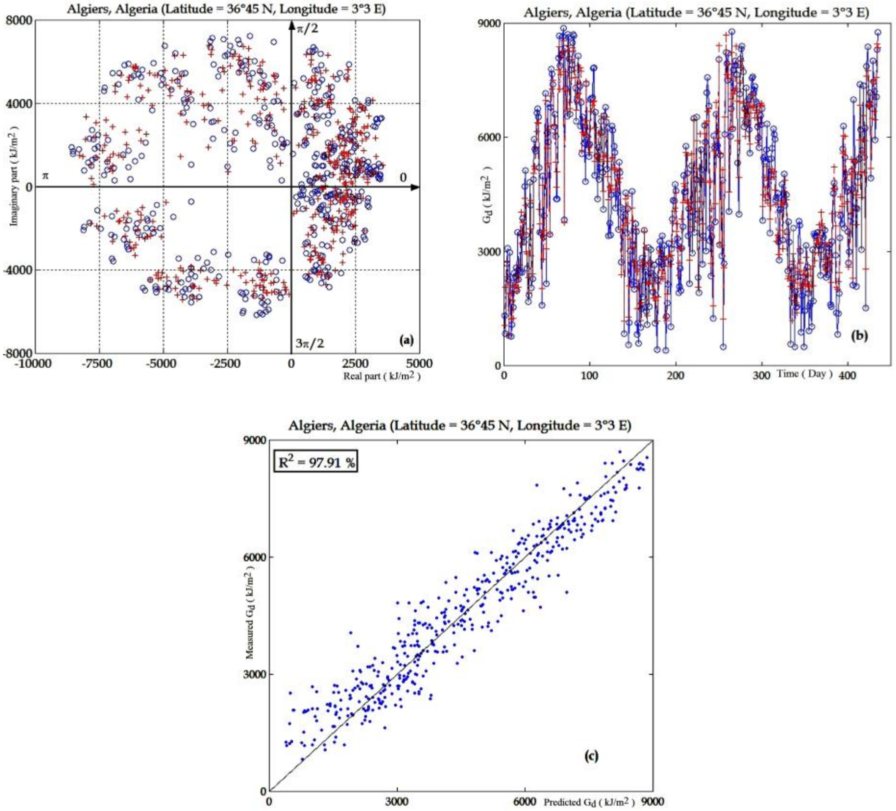


Fig. 4: Measured and predicted daily solar irradiation for 15 days in the city Algiers (a) in the polar plane, (b) temporal and (c) measured versus predicted

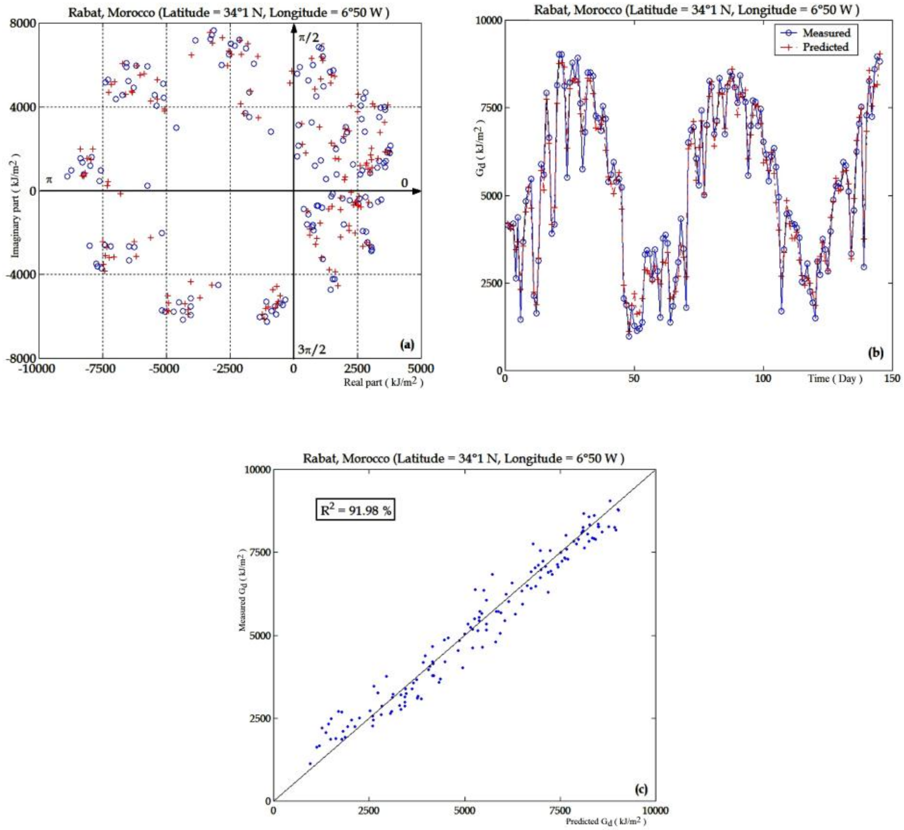
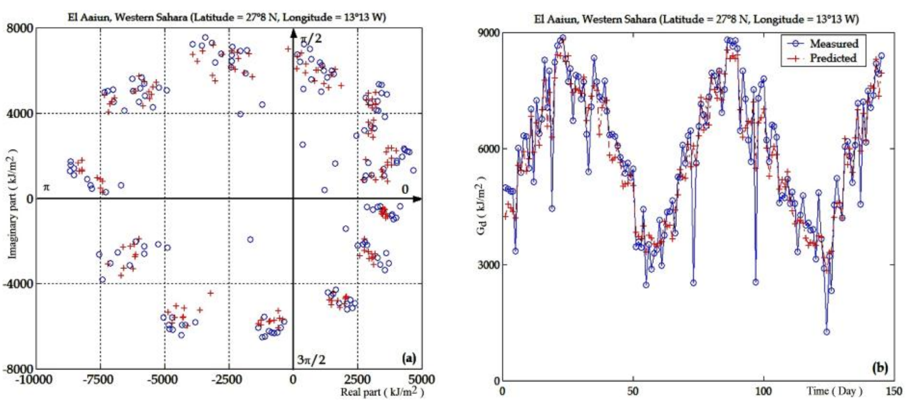


Fig. 5: Measured and predicted daily solar irradiation for 15 days in the city Rabat (a) in the polar plane, (b) temporal and (c) measured versus predicted



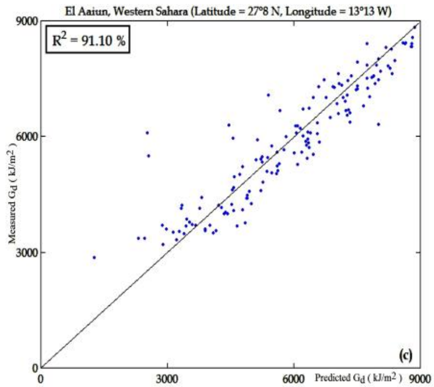


Fig. 6: Measured and predicted daily solar irradiation for 5 days in the city El Aaiun (a) in the polar plane, (b) temporal and (c) measured versus predicted

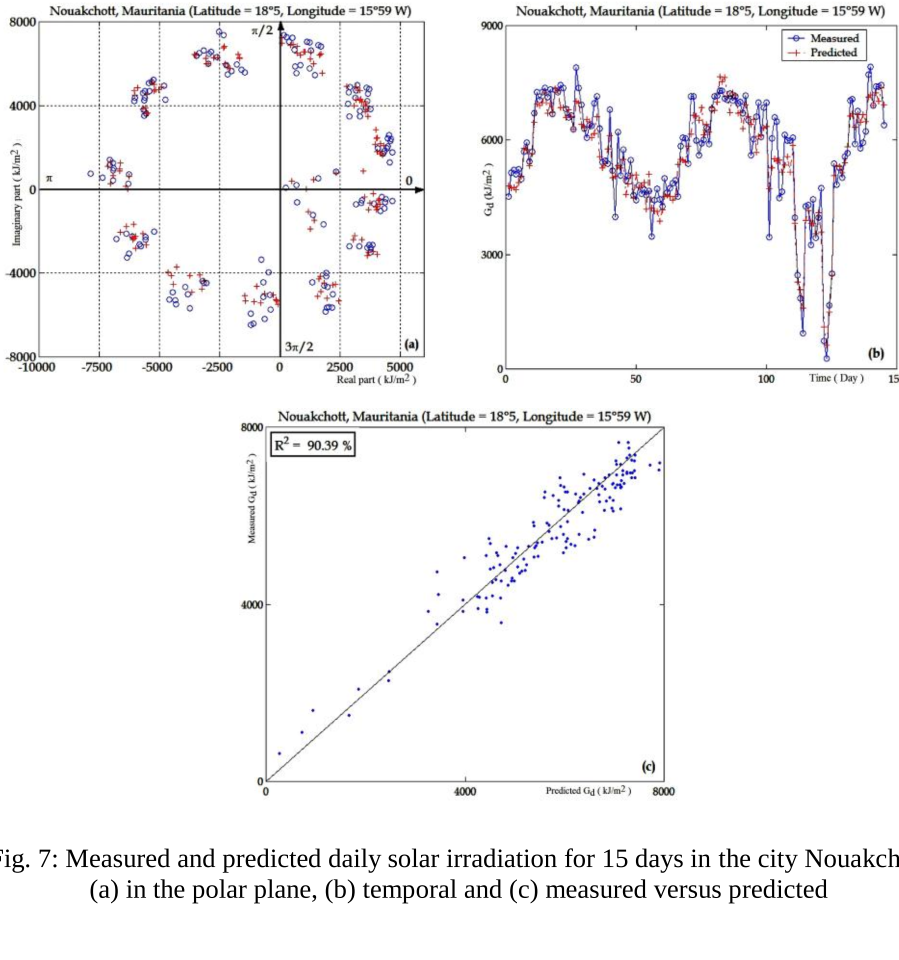


Fig. 7: Measured and predicted daily solar irradiation for 15 days in the city Nouakchott (a) in the polar plane, (b) temporal and (c) measured versus predicted

5. CONCLUSION

In this work, the application of the complex-valued neural networks to predict the daily solar irradiation for the great Maghreb region is presented. The CVNN models have been validated using satellite data in the Great Maghreb, whose capitals are: Tripoli (Libya), Tunis (Tunisia), Algiers (Algeria), Rabat (Morocco), El Aaiun (Western Sahara) and Nouakchott (Mauritania), were selected for the collection of data. The CVNN proves its abilities to predict the daily solar irradiation in both cases (MISO and MIMO strategies) for all cities.

ACKNOWLEDGMENTS

This work is supported by the National Committee for Evaluation and Planning Unit of University Research, Ministry of Higher Education and Scientific Research, Algeria, under projects' numbers: J0200320090014 and J0200320130025.

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