Quaternion neural network to forecast the daily solar irradiation

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Abstract

In this paper, the quaternion neural network for forecasting the daily solar irradiation is proposed. A method to transform the complex valued daily meteorological parameters to quaternion numbers is presented. This method gives the opportunity to forecast the daily solar irradiation using one quaternion input rather than two inputs, which decrease the input dimension vector. The results are obtained for quaternion parameter input that contains the combination of two meteorological parameters (the air temperature and the relative humidity, the air temperature and the sunshine duration or the relative humidity and the sunshine duration). Comparison with complex valued neural network for forecasting the daily solar irradiation shows that the method proposed in this paper is suitable to deal with such problem.

Key words: quaternion neural network, daily solar irradiation, forecasting, complex valued neural network.

1. Introduction

Quaternion Valued Neural Networks (QVNNs) are one of the promising methods for modeling nonlinear systems in four dimensions naturally [1, 2, 3, 4, 5, 6, 7]. Quaternion number is a four-dimensional hypercomplex number system introduced by Hamilton [8, 9]. All the network's parameters (i.e. weighs, bias, inputs and outputs) are quaternion numbers [10] (i.e. they belong to Hamiltonian domain $\mathbb{H}$). Two main advantages could be obtained when using QVNNs: 1) the numbers of inputs and outputs are reduced four times comparing to real valued modeling strategy. 2) three other dimension are added to the real valued learning algorithm. In literature, the QVNNs have found primordial place in real world application. For instance, Shang and Hirose [11] used the QVNN to classify images coming from radar and they prove the QVNN's ability for detecting the lake, grass, forest, and town areas. The adaptive filtering based on the QVNN has proposed in [12]. The QVNNs have been applied successfully in image processing in [13, 14] and gait recognition using the magnitude and phase of quaternion wavelet transform in [15]. The application of QVNN has been investigated to robot manipulator control in [16]. Wong et al. [17] used the quaternion for the thermal condition monitoring system and the application of the quaternions and octonions in mechanics is presented in [18].
In this paper, the quaternion neural networks are used for forecasting one-day ahead of the daily

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solar irradiation combining two meteorological parameters (the air temperature and the relative humidity, the air temperature and the sunshine duration or the relative humidity and the sunshine duration). The quaternion backpropagation algorithm [10], which is the extended version of the well-known real valued backpropagation is outlined.

2. Global solar irradiation forecasting and proposition of new method

In literature, several techniques and models have been proposed for forecasting the global solar irradiation, where neural networks occupied a great part. In [19, 20, 21, 22, 23, 24, 25, 26], the total solar radiation time series simulated using neural networks. The prediction of maximum solar radiation using artificial neural networks is presented in [22, 27].The monthly mean daily values of global solar radiation on horizontal surfaces prediction using neural networks is investigated in [22, 28, 29]. The neural networks have been also used to estimate the daily solar irradiation in [30, 31, 32, 33, 34, 35] and the hourly solar irradiation [36, 37, 38, 39, 40, 41, 42, 43].

In other recent works [44, 45, 46, 47] a method combining the image processing and the solar irradiation is proposed. The idea is to present the solar irradiation with both time indexes (days of the year in one axis and the hours of the day in the second axis). The obtained representation will be converted to the 2-D gray-scale image that will be further interpreted using image processing techniques.

The complex valued neural network are used to forecast the complex valued global solar irradiation (in the daily and the hourly time indexes) of Tamanrasset city (Algeria) in [48] and for the whole Maghreb region (in the daily time index) in [49]. In [50], the complex valued wavelet neural network has been applied to forecast the daily solar irradiation based on the other meteorological data. For example, in our previous work [48], we have proposed the complex valued neural network based forecasting the daily and the hourly solar irradiation. The meteorological variables (the daily solar irradiation, the daily temperature, the relative humidity, and the sunshine duration) are used as inputs to the network. The better results are obtained using the daily solar irradiation and the daily temperature as network inputs to forecast the 24 hours ahead of the solar irradiation.

The use of the complex valued neural network to forecast the solar irradiation [48] permit the reduction of the inputs and have the time indexes integrated with data itself. According to the fact that time is very useful for the modeling of periodic components of the series, such as those exhibited by solar radiation [51].

In this paper, we use quaternion neural network to forecast the daily solar irradiation using the meteorological data. First, we construct the complex valued (CV) daily meteorological data as we have done in our previous work [48]. Besides, we use two complex valued meteorological data to construct one quaternion valued meteorological parameter.

Let us take a quaternion number:

$$q \stackrel{def}{=} x_1 + ix_2 + jx_3 + kx_4 \tag{1}$$

Where: $x_1, x_2, x_3, x_4 \in R$

$$i^2 = j^2 = k^2 = ijk = -1 \text{ and } ij = k, jk = i, ik = j, ji = -k, kj = -i, ki = -j$$

For instance, if we want to forecast the daily solar irradiation using the day number, the air

temperature and relative humidity, we use $x_1 = real(T_m)$, $x_2 = Imag(T_m)$, $x_3 = real(H_m)$, $x_4 = Imag(H_m)$ to realize the quaternion number.
Where: T_m is the complex valued air temperature and H_m is the complex valued relative humidity.

3. Quaternion valued neural network

The quaternion valued neural network is used to forecast one day ahead of the daily solar irradiation based on the values of different quaternion valued meteorological data of the actual day. Each input contains two meteorological data converted before into complex domain. This architecture is represented in figure (1). The network has three layers: the first one represents the input layer that can receive the quaternion valued combined parameters (CV air temperature and CV relative humidity, or CV air temperature and CV sunshine duration, or CV sunshine duration and CV relative humidity), one hidden layer has *m* neurons and an output layer represents the daily solar irradiation. These layers are connected together with weights w^1_{nm} and w^2_m. The hidden and the output layers have bias w^1_{0m} and w^2_0. All the network parameters, the inputs and the outputs are quaternion valued. It should be noted that the multiplication of two quaternions is not commutative (i.e. $\forall q_1, q_2 \in H$, $q_1 q_2 \neq q_2 q_1$), but it is associative.

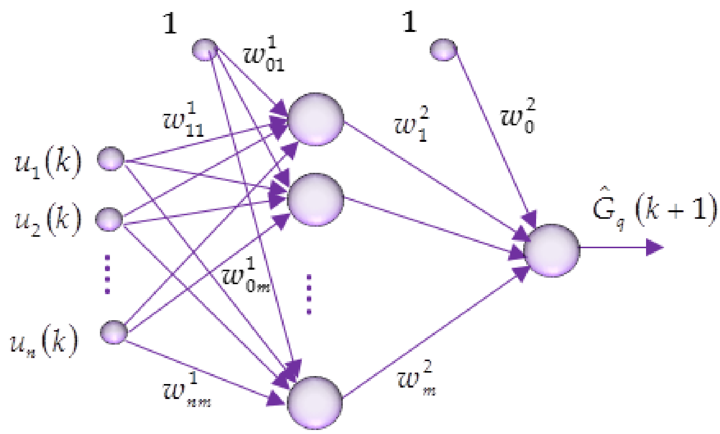

Figure 1. Quaternion valued neural network to forecast one-day ahead solar irradiation.

The QVNN output could be calculated using the following equation:

$$\hat{G}_q(k+1) = f^2\left(\tilde{y}^{\mathrm{Re}}\right) + i\, f^2\left(\tilde{y}^{\mathrm{Im}(i)}\right) + j\, f^2\left(\tilde{y}^{\mathrm{Im}(j)}\right) + k\, f^2\left(\tilde{y}^{\mathrm{Im}(k)}\right) \tag{2}$$

Where: the subsets *Re*, Im(*i*), Im(*j*) and Im(*k*) represent the real part, the imaginary parts according to *i*, *j* and *k*, respectively. f^2 is the sigmoid nonlinear function given by the following equations:

$$f^2(\cdot) = \frac{1}{1+e^{-(\cdot)}} \tag{3}$$

$$\tilde{y} = \sum_{l=1}^{m} w^2_l h_l + w^2_0 \tag{4}$$

Where: l=1, …, m.

h_l is the l^{th} hidden neuron's output given by equation (5).

$$h_l = f^1\left(\tilde{h}_l^{\mathrm{Re}}\right) + i\, f^1\left(\tilde{h}_l^{\mathrm{Im}(i)}\right) + j\, f^1\left(\tilde{h}_l^{\mathrm{Im}(j)}\right) + k\, f^2\left(\tilde{h}_l^{\mathrm{Im}(k)}\right) \tag{5}$$

With $\tilde{h}_l$ is given by:

$$\tilde{h}_l = w_{nl}^1 u_n + w_{0l}^1 \tag{6}$$

u_n is the quaternion valued vector of the meteorological data.

The quaternion valued backpropagation algorithm [10], which is quaternion version of the real backpropagation algorithm, is used to train the network's parameters.

The objective is to find the network's parameters that minimizes the sum-squared error at the output layer which can be written as

$$E = \frac{1}{2} e^H e = \frac{1}{2} \sum_d e_d e_d^* = \frac{1}{2} \sum_d E_d \tag{7}$$

$$E_d = e_d e_d^* = \left|e_d\right|^2 \tag{8}$$

The subset '*' represents the conjugate operator and H is the Hermitian operator. d is the number of samples.

$$\begin{aligned} e &= G_q(k+1) - \hat{G}_q(k+1) \\ &= e^{\mathrm{Re}} + ie^{\mathrm{Im}(i)} + je^{\mathrm{Im}(j)} + ke^{\mathrm{Im}(k)} \end{aligned} \tag{9}$$

Where e is the error between the desired output G_q and the estimated output $\hat{G}_q$ and e^* is the error's conjugate.

The quaternion valued gradient descent with momentum algorithm is used to find the optimal parameters of the QVNN and is given as follows:

For the bias w_0^2:

Let's take:

$$w_0^2 = w_0^{2\,\mathrm{Re}} + iw_0^{2\,\mathrm{Im}(i)} + jw_0^{2\,\mathrm{Im}(j)} + kw_0^{2\,\mathrm{Im}(k)}.$$

$$\nabla_{w_0^2} E = \frac{\partial E}{\partial w_0^{2\,\mathrm{Re}}} + i\frac{\partial E}{\partial w_0^{2\,\mathrm{Im}(i)}} + j\frac{\partial E}{\partial w_0^{2\,\mathrm{Im}(j)}} + k\frac{\partial E}{\partial w_0^{2\,\mathrm{Im}(k)}} \tag{10}$$

$$\begin{aligned} \nabla_{w_0^2} E = -\Big\{ & e^{\mathrm{Re}}\left(1 - G_q^{\mathrm{Re}}\right)\cdot G_q^{\mathrm{Re}} + ie^{\mathrm{Im}(i)}\left(1 - G_q^{\mathrm{Im}(i)}\right)\cdot G_q^{\mathrm{Im}(i)} \\ & + je^{\mathrm{Im}(j)}\left(1 - G_q^{\mathrm{Im}(j)}\right)\cdot G_q^{\mathrm{Im}(j)} + ke^{\mathrm{Im}(k)}\left(1 - G_q^{\mathrm{Im}(k)}\right)\cdot G_q^{\mathrm{Im}(k)} \Big\} \end{aligned} \tag{11}$$

$$w_0^2(k+1) = w_0^2(k) - \eta \nabla_{w_0^2} E \tag{12}$$

For the weights w_l^2, where

$$w_l^2 = w_l^{2\,\mathrm{Re}} + iw_l^{2\,\mathrm{Im}(i)} + jw_l^{2\,\mathrm{Im}(j)} + kw_l^{2\,\mathrm{Im}(k)}.$$

$$\nabla_{w_l^2} E = \frac{\partial E}{\partial w_l^{2\,\mathrm{Re}}} + i\frac{\partial E}{\partial w_l^{2\,\mathrm{Im}(i)}} + j\frac{\partial E}{\partial w_l^{2\,\mathrm{Im}(j)}} + k\frac{\partial E}{\partial w_l^{2\,\mathrm{Im}(k)}} \tag{13}$$

$$\begin{aligned} \nabla_{w_l^2} E = -h_l^* \cdot \Big\{ & e^{\mathrm{Re}}\left(1 - G_q^{\mathrm{Re}}\right)\cdot G_q^{\mathrm{Re}} + ie^{\mathrm{Im}(i)}\left(1 - G_q^{\mathrm{Im}(i)}\right)\cdot G_q^{\mathrm{Im}(i)} \\ & + je_l^{\mathrm{Im}(j)}\left(1 - G_q^{\mathrm{Im}(j)}\right)\cdot G_q^{\mathrm{Im}(j)} + ke^{\mathrm{Im}(k)}\left(1 - G_q^{\mathrm{Im}(k)}\right)\cdot G_q^{\mathrm{Im}(k)} \Big\} \end{aligned} \tag{14}$$

$$w_l^2(k+1) = w_l^2(k) - \eta \nabla_{w_l^2} E \tag{15}$$

The same procedure is used for the bias w_{0l}^1 and weights w_{nm}^1, where:

$$w_{0l}^1 = w_{0l}^{1\mathrm{Re}} + i w_{0l}^{2\,\mathrm{Im}(i)} + j w_{0l}^{1\,\mathrm{Im}(j)} + k w_{0l}^{1\,\mathrm{Im}(k)}$$
$$w_{nm}^1 = w_{nm}^{1\mathrm{Re}} + i w_{nm}^{1\,\mathrm{Im}(i)} + j w_{nm}^{1\,\mathrm{Im}(j)} + k w_{nm}^{1\,\mathrm{Im}(k)},$$

hence the adaptation method is given as follows:

$$\nabla_{w_{0l}^1} E = \frac{\partial E}{\partial w_{0l}^{1\mathrm{Re}}} + i \frac{\partial E}{\partial w_{0l}^{1\,\mathrm{Im}(i)}} + j \frac{\partial E}{\partial w_{0l}^{1\,\mathrm{Im}(j)}} + k \frac{\partial E}{\partial w_{0l}^{1\,\mathrm{Im}(k)}} \tag{16}$$

$$\begin{aligned}\nabla_{w_{0s}^1} E = -\Big\{ & \left(1-h_l^{\mathrm{Re}}\right)\cdot h_l^{\mathrm{Re}} \cdot \nabla_{w_0^2} E \cdot w_l^{2*} \left(\nabla_{w_0^2} E \cdot w_l^{2*}\right)^{\mathrm{Re}} + i\left(1-h_s^{\mathrm{Im}(i)}\right)\cdot h_s^{\mathrm{Im}(i)} \cdot \left(\nabla_{w_0^2} E \cdot w_l^{2*}\right)^{\mathrm{Im}(i)} \\ & + j\left(1-h_l^{\mathrm{Im}(j)}\right)\cdot h_l^{\mathrm{Im}(j)} \cdot \left(\nabla_{w_0^2} E \cdot w_l^{2*}\right)^{\mathrm{Im}(j)} + k\left(1-h_l^{\mathrm{Im}(k)}\right)\cdot h_l^{\mathrm{Im}(k)} \cdot \left(\nabla_{w_0^2} E \cdot w_l^{2*}\right)^{\mathrm{Im}(k)} \Big\}\end{aligned} \tag{17}$$

$$w_{0l}^1(k+1) = w_{0l}^1(k) - \eta \nabla_{w_{0l}^1} E \tag{18}$$

$$\nabla_{w_{nl}^1} E = \frac{\partial E}{\partial w_{nl}^{1\mathrm{Re}}} + i \frac{\partial E}{\partial w_{nl}^{1\,\mathrm{Im}(i)}} + j \frac{\partial E}{\partial w_{nl}^{1\,\mathrm{Im}(j)}} + k \frac{\partial E}{\partial w_{nl}^{1\,\mathrm{Im}(k)}} \tag{19}$$

$$\nabla_{w_{nl}^1} E = -u_n^* \cdot \nabla_{w_{nl}^1} E \tag{20}$$

$$w_{nl}^1(k+1) = w_{nl}^1(k) - \eta \nabla_{w_{nl}^1} E \tag{21}$$

With: η is the learning rate.

Note that the conjugate of a quaternion number is given as follows:

$$q^* \overset{def}{=} x_1 - i x_2 - j x_3 - k x_4 \tag{22}$$

3. Results

The QVNN is used to forecast one-day ahead of the solar irradiation using obtained quaternion valued meteorological data. Firstly, we use just one input that contains a combination of two meteorological data. Besides, we applied two quaternion inputs (i.e. three meteorological data and one delayed complex value of the daily solar irradiation).

The measured data, obtained from the national meteorological center of Algeria, corresponding to Tamanrasset city, Algeria (latitude: 22°48 N; longitude: 05°26 E) is used. The procedure described in [48] is used to obtain the complex valued form of the daily global solar irradiation G_q, the daily air temperature T_m, the relative humidity H_m and the sunshine duration S_m. To make the data useful to the QVNN, it should be transformed into the quaternion-valued domain. The combination of two complex valued parameters can produce one quaternion parameter. In all cases, we have used 11 months (year 2007) to train the QVNN and the last month (December 2007) for validation. All the network has two neurons in the hidden layer. To evaluate the performance of the proposed technique, we use the normalized root mean squared error (nRMSE) and mean absolute error (MAE) like criteria.

The obtained results are shown in Table (1). One can see that the air temperature and the sunshine duration give the best results and the introduction of the relative humidity decreases the quality. In addition, the air temperature influences the result's quality, according to the fact that when we do not use this parameter as input the performance is decreased.

Figure (2) shows the measured and the forecasted output for the case of one QVNN with one input contains the air temperature and the sunshine duration. The corresponding error is shown in figure (3). The correlation plot between the measured versus the forecasted daily solar irradiation is presented in figure (4).
According to the obtained results, we can say the QVNN is preferable to forecast the daily solar irradiation.

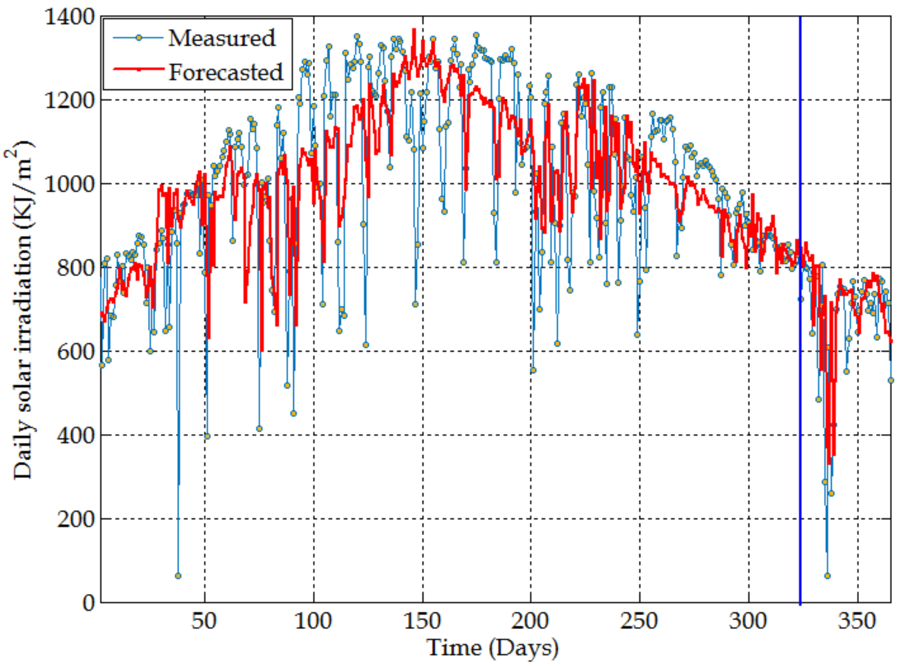

Figure 2. Measured and forecasted daily solar irradiation for Tamanrasset city.

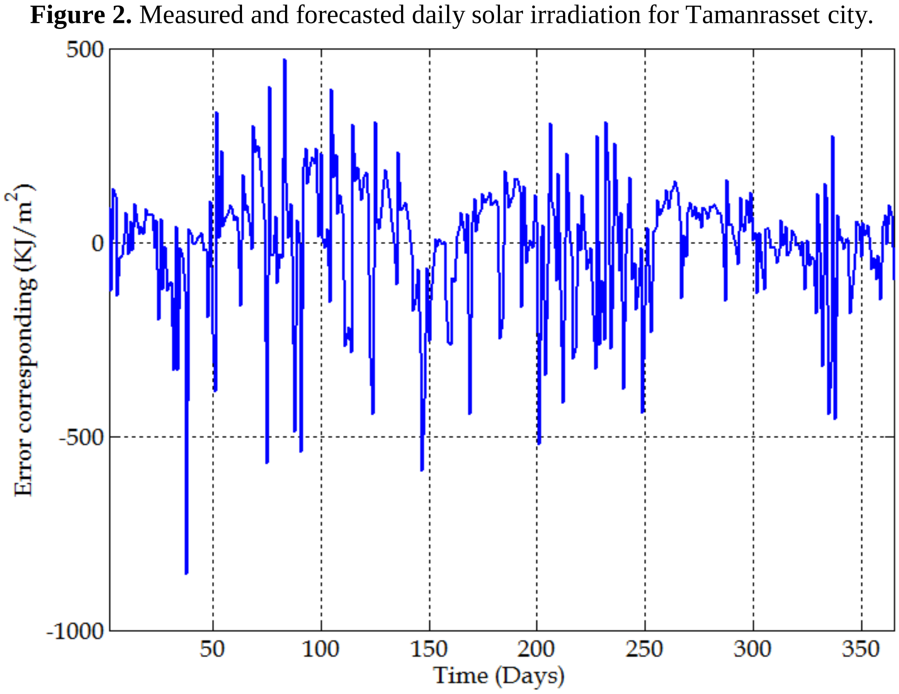

Figure 3. The corresponding error.

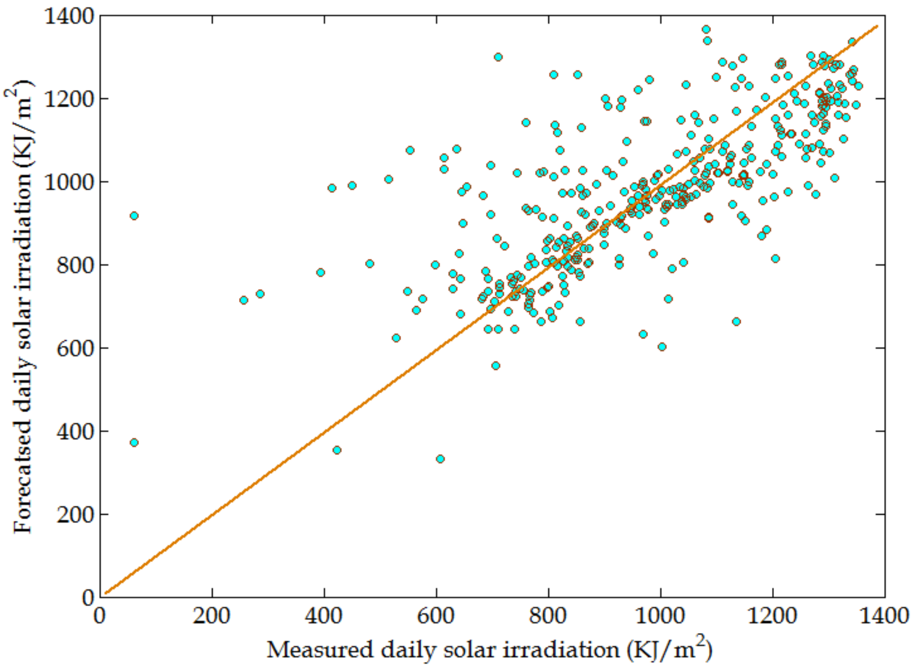

Figure 4. The correlation between the measured versus forecasted daily solar irradiation.

Table 1. Results for Forecasting one-day ahead of the daily solar irradiation using different meteorological data

Structure	MAE (%)	nRMSE (%)
$\hat{G}_q(k+1)=f\{S_m(k),T_m(k)\}$	0.40	4.01
$\hat{G}_q(k+1)=f\{T_m(k),H_m(k)\}$	0.95	9.54
$\hat{G}_q(k+1)=f\{S_m(k),H_m(k)\}$	1.12	11.80
$\hat{G}_q(k+1)=f\{T_m(k),S_m(k),H_m(k),G_q(k)\}$	0.62	6.62

Conclusions

In this work, the forecasting of the daily solar irradiation using the quaternion valued neural network is proposed. The meteorological data was converted to complex valued parameters, thereby; the realization of quaternion variable is achieved. The use of the QVNN to forecast the daily solar irradiation has an important advantage, which is the reduction of the input vector's dimension comparing to the complex valued neural network (e.g. use the air temperature and the sunshine duration at the same time in one input, rather that two complex valued parameters in the complex valued neural networks). The obtained results show that using the air temperature with other meteorological parameters is very important. The relative humidity decreases the forecasting quality and the sunshine duration has a mandatory influence. As perspective work, we try to use other structures, such as the parallel forecasting (i.e. predicting several days ahead).

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