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# Short-term multi horizons forecasting of solar irradiation based on artificial neural network with meteorological data : Application in the north-west of Senegal

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**Abstract**—This study proposes a short term forecasting of solar irradiation with multi horizons in the north-west of Senegal. The multilayer artificial neural network (ANN), based on the Levenberg Marquardt algorithm and the meteorological data are used. The latter are measured in real time on the study site. The variables of interest are: mean solar irradiation, maximum temperature and measurement time; they are selected using Weka software. The forecasting horizons are: 0.5 hour, 1 hour, 1.5 hours, 2 hours, 2.5 hours, 3 hours, 3.5 hours, 4 hours, 4.5 hours, 5 hours, 5.5 hours and 06 hours. They are proposed with the corresponding statistical criteria. The results show that, the solar energy forecasting can be extended over a six-hour horizon with a correlation coefficient of 0.97 and root mean square error of 0.07. These results will make it possible to complete the forecasting tools in the solar energy sector in Senegal, and help investors to choose the most suitable horizons for energy forecasting in photovoltaic solar power plants.

**Keywords**—solar irradiation, neural network, levenberg-marquardt, multi horizons, forecasting.

## I. INTRODUCTION

Renewable energies have experienced significant growth for several decades due to their positive impact on the environment [1]. In the most developing countries, electrical energy is largely supplied by power grids and associated power plants that are often inefficient and unreliable due to poor maintenance [2]. One of the economic consequences is the low rate of rural electrification, the high cost per kWh in rural areas and the unavailability of electricity for the income-generating activities. To address these issues, the use of renewable energy is an important part of the solution. To this end, several works are proposed in the literature in order to exploit the renewable resource: wind and solar power potential assessment [2], sizing of solar panels and wind turbines [3], control and command [4], energy demand forecasting [5] and available energy forecasting. In this work, we are interested in the last category.

Energy forecasting offers the possibility to guarantee its availability in order to meet current and future needs.

The works [6] has classified the forecasting models into several horizons: the short term ([second - 06 h]), the medium term ( ]06h-24h]) and the long term (1 week and more). We are interested in forecasting solar irradiation over the short term.

Forecasting models are classified into three main categories [7]: physical, statistical and intelligent models. A comparative studies of these models indicate that, artificial intelligence is very suitable for forecasting the solar energy resource and allows to obtain good results [1]. The most used artificial intelligence models are: artificial neural network (ANN), support vector machine and fuzzy logic. The ANN is ranked as the best and most used forecasting model [8]. In this work, the ANN is used for forecasting solar irradiation over several short-term horizons.

The artificial neural network has the particularity of managing a large volume of data. Its four basic principles are [6] : the network typology, the type of association between input and output variables, the data training method and the forecasting output presentation. In the literature, several methods are used to select the network typology needed to train the ANN model: system for automated learning operative networks (Salmon) [9], Bayesian method [10], R development core team [11] and the Waikato software for knowledge analysis (Weka) [12]. In addition to providing the network typology and choosing the variables of interest, Weka offers the possibility to choose the number of hidden layers for ANN training. ANN performance is evaluated according to several criteria [13] : correlation coefficient (R), root mean square error (RMSE), normal root mean square error (nRMSE), mean bias error (MBE), mean absolute percentage error (MAPE) and statistical time indicator (t-statistic).

The objective of this work is to establish and classify short-term forecasting models of solar irradiation along several horizons in north-western Senegal. The horizons vary from 0.5 hour to six hours. Each horizon is validated based on its performance criteria. The results will help address the problems of energy demand and production in Senegal. Indeed, 75 % of the population in Senegal lives in rural areas and more than 50 % has no access to electricity. In order to respond to the electrification problems, several solar power plants have been built in recent years, but are struggling to balance energy production with user energy demand; a major cause of this shortage is the intermittency of the solar resource.

To date, very few forecasting models have been developed in Senegal to address the problem of solar resource's intermittency. The short-term forecasting models over several time horizons, proposed in this paper, will complete the existing works.

The works [14] has developed a short-term forecasting model for wind potential in the north-west of Senegal using linear prediction, with a correlation coefficient of 0.86. Solar irradiation short-term forecasting, applied to north-western Senegal is developed in [15] with a correlation coefficient of 0.99; the authors have limited the horizon to 10 min. To complete this limit, we propose forecasting models for short-term horizons from 30 minutes to 06 hours. Using Kalman filters, solar potential forecasting is carried out over a 20-minute horizon in Dakar [16] ; the results are obtained with a normal quadratic error of 4.8%. The works [17] studied short-term forecasting of solar potential in Dakar using the autoregressive moving average (ARMA) method; annual meteorological data from the "École Supérieure Polytechnique Dakar" were used; the results show a correlation coefficient of 0.97 and a root mean square error (RMSE) of 0.629. To solve the problem of energy demand in Senegal, electricity forecasting on one hour horizon is proposed in the works [18]. The data used are the times of sunny days and hourly weather data. The results are obtained with a correlation coefficient of 0.9. Using R Software and satellite data, the work [19] carried out solar irradiation forecasting in several regions of Senegal: Dakar, Saint-Louis, Tambacounda and Ziguinchor. The forecasting performance showed a mean square error of 20%. The solar potential forecasting over a 20 minute horizon in Dakar using solar irradiation data on the one hand, and the solar irradiation, humidity and temperature on the other hand is carried out using the Kalman filter in [20]. The results are obtained with a normal root mean square error of 4.9% and 4.8% respectively.

The above forecasting models, developed in Senegal are based on a single time horizon, which do not leave investors and decision-makers the option of choosing the energy forecasting horizons corresponding to users demand. To make an additional contribution to the existing works, we propose in this paper:

- the different meteorological variables and their influence on short-term forecasting accuracies;
- Twelve short-term forecasting models with horizons ranging from 30 minutes to six hours. It is the originality of this study. It will complete

our previous work in which the horizon was limited to 10 minutes. It will allow investors and solar power plants owners to choose the forecasting horizons by taking into account the energy demand, the availability and the capacity of the measurement infrastructures collecting and storing the data.

The rest of the paper is organized as follows: section 2 presents the study environment and the data presentation. Section 3 describes and presents the method; section 4 is devoted to the results and discussion. The final section presents the conclusion and perspectives.

## II. STUDY ENVIRONMENT AND DATA PRESENTATION

The studied environment is located in the north-west of Senegal. This environment has a strong solar potential ranging from  $3756Wh/m^2/day$  in December to  $6420Wh/m^2/day$  in April. The data are from the Gandon site, located between  $15^{\circ}26'50''$  of the northern altitude and  $16^{\circ}26'49''$  eastern longitude. The meteorological data used are measured and averaged in 10 min steps; they are: number of the day (Dn), time of measurement (h), maximum (Tm) and average (T) temperature, maximum (Hm) and average (H) relative humidity, maximum (Em) and average (E) solar irradiation, atmospheric pressure (P). These data are presented and detailed in our previous work [15].

## III. METHODS

The synoptic diagram used for solar irradiation forecasting is shown in Figure 1

### A. Selection of the interest variables and the hidden layers number

The variables of interest are selected using Weka software. It is a software developed by the University of Waikato, adapted for machine learning and data mining. It helped to establish:

- the contribution of each variable on the solar irradiation forecasting accuracy over the  $\Delta T$  horizon,
- the contribution of the variables combination on solar irradiation forecasting accuracy over the  $\Delta T$  horizon,
- the choice of the hidden layers number.

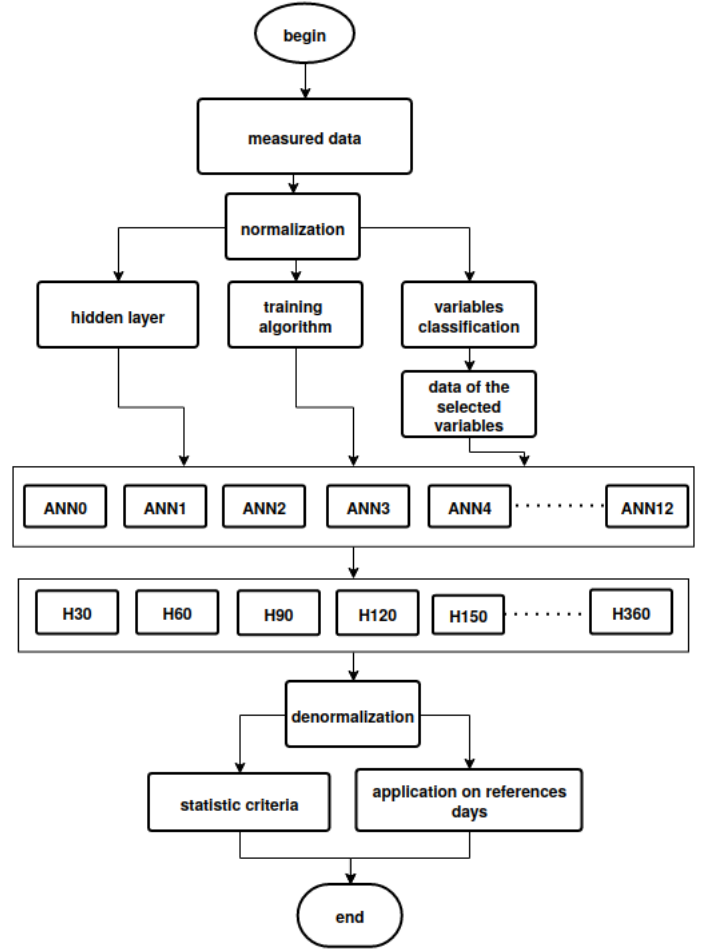


Figure 1. ANN synoptic diagram

### B. data normalization and denormalization

Large input values associated with small values can compromise the learning step leading to local sub-optimization [21]. To avoid this problem, authors [22] recommend to use normalized data for training ANN. This method consists in improving the ANN performance and convergence [9].

Equation (1) is used for data normalization:

- $x$  : the measured variable
- $y$  the normalized value of the measured variable
- $x_{max}$  the measured variable's maximum value
- $x_{min}$  the measured variable's minimum value
- $y_{min}$  the normalized variable's minimum value
- $y_{max}$  the normalized variable's maximum value

$$y = \frac{(y_{max} - y_{min})(x - x_{min})}{(x_{max} - x_{min})} + y_{min} \quad (1)$$

After training the artificial neural network model, the data are denormalized using equation(2). Denormalization consists in bringing the normalized data to the

normal values.

$$x = \frac{(x_{max} - x_{min})(y - y_{min})}{(y_{max} - y_{min})} + x_{min} \quad (2)$$

### C. Artificial neural network

The ANN typology used is the feed-forward multi-layer perceptron neural network. Its internal configuration as well as the training equations (the levenberg-marquardt algorithm) are presented in [15]. The ANN architecture and the training flowchart for each horizon are presented respectively on Figure 2 and Figure 3

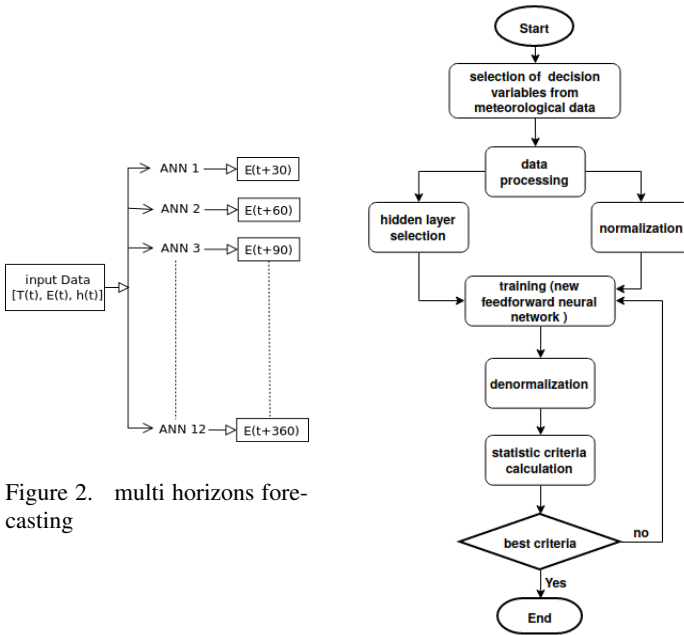


Figure 2. multi horizons forecasting

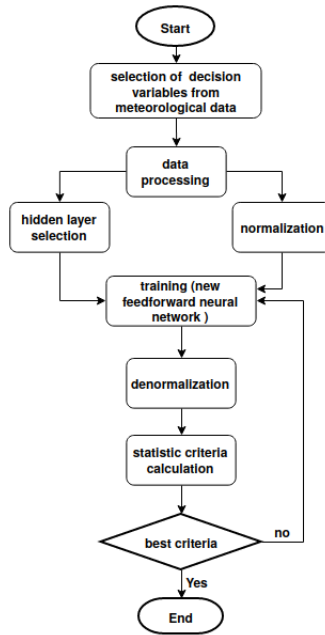


Figure 3. ANN training

## IV. ANN STATISTICAL CRITERIA

ANN performance are calculated using Eq.(3) [13]; Eq.(4),Eq.(5) [21]; Eq.(6),Eq.(7) [13].

- $x_i$  the  $i^{th}$  measured data
- $\hat{x}_i$  the  $i^{th}$  forecasted data
- $E(x)$  the average of the test data
- $N$  total number of test data

$$R^2 = 1 - \frac{\sum_i (x_i - \hat{x}_i)^2}{\sum_i (x_i)^2} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_i (x_i - \hat{x}_i)^2}{N}} \quad (4)$$

$$nRMSE = \frac{RMSE}{E(x)} \quad (5)$$

$$MBE = \frac{1}{N} * \sum_i (\hat{x}_i - x_i) \quad (6)$$

$$t - statistic = \sqrt{\frac{(N - 1)MBE^2}{RMSE^2 - MBE^2}} \quad (7)$$

### A. reference days

A reference day is calculated for each month of the year. Forecasting performance is evaluated for each reference day. This latter is defined as the closest to the monthly average data [14]. Let  $E_{i,j,h}$  be the solar irradiation measured at time  $h$  of day  $j$  in the month  $i$ .

- $h$  the time corresponding to the measurement of the day  $j$  ;
- $j$  the number of the day in the month  $i$
- $i$  the number of the month in the year ;
- $h \in \{10, 20, \dots, 1440\}$
- $j \in \{1, 2, \dots, 31\}$
- $i \in \{1, 2, \dots, 12\}$ .

The solar irradiation  $E_{i,j}$  of the day  $j$  in the month  $i$  is given by equation (8)

$$E_{i,j} = [E_{i,j,10}, E_{i,j,20}, \dots, E_{i,j,1440}]^T \quad (8)$$

The average value of solar irradiation  $\bar{E}_{i,h}$  at time  $h$  is calculated by the equation (9)

$$\bar{E}_{i,j} = \sum_{j=1}^{N_i} \frac{E_{i,j,h}}{N_i} \quad (9)$$

the average day  $\bar{E}_i$  of the month  $i$  is defined by equation10

$$\bar{E}_i = [\bar{E}_{i,10}, \bar{E}_{i,20}, \bar{E}_{i,30}, \dots, \bar{E}_{i,1440}]^T \quad (10)$$

$N_i$  is the data number of the month  $i$ . The solar irradiation on reference days  $j_i$  of each month  $i$  is the closest to  $\bar{E}_i$  [14].

## V. RESULTS AND ILLUSTRATION

The values of  $y_{max}$  and  $y_{min}$  are chosen equal to one and zero respectively.

### A. Selection of interest variables and number of layers

The correlation between the meteorological variables and solar irradiation forecasting accuracy over a  $\Delta T$  horizon are presented in Table I. R denotes the correlation coefficient. The mean solar irradiation, maximum temperature and measurement time are chosen as the final input for the ANN.

Table I. INFLUENCE OF METEOROLOGICAL VARIABLES ON THE MEAN SOLAR IRRADIATION FORECASTING

interests variables real time (t)	R (%) horizon ( $t + \Delta T$ )
P	05.21%
Dn	10.06%
Hm	43.76%
H	44.44%
h	52.41%
T	66.76%
Tm	67.27%
h, T	67.81%
h, Tm	68.33%
T, Tm	69.89%
h, T, Tm	94.66%
Em	98.09%
T, Em	98.11%
Tm, Em	98.11%
he, Em	98.12%
T,Tm,Em	98.21%
h, T, Em	98.36%
h, Tm, Em	98.36%
h,T,Tm,Em	98.36%
E	98.85%
E, Em	98.85%
h, E	98.86%
T,E	98.88%
Tm,E	98.88%
T,Tm,E,Em	99.01%
T,Tm, E	99.01%
Tm,E,Em	99.01%
h, T, E	99.06%
h, Tm, E	99.06%
h,T,Tm,E	99.06%
h,E,Em	99.1%
h,Tm,E,Em	99.1%
h,T,Tm H,Hm,E,Em	99.15%

Table II. ANN TRAINING PERFORMANCE

horizons (min)	training	validation	test	training regression
30	0.98	0.981	0.982	$y=0.96x+0.0075$
60	0.973	0.975	0.975	$y=0.95x+0.0093$
90	0.968	0.970	0.969	$y = 0.94 x+0.012$
120	0.965	0.961	0.968	$y=0.93x+0.013$
150	0.959	0.954	0.959	$y=0.92x+0.014$
180	0.957	0.956	0.954	$y=0.91x+0.015$
210	0.953	0.950	0.949	$y=0.91x+0.017$
240	0.950	0.948	0.945	$y=0.9x+0.018$
270	0.947	0.947	0.941	$y=0.9x+0.019$
300	0.945	0.943	0.942	$y=0.89x+0.02$
330	0.941	0.938	0.942	$y=0.89x+0.021$
360	0.941	0.936	0.940	$y=0.89x+0.021$

B. ANN training step

70 % of the data are used for training ANN. Results are presented in tableII.

The first item in the Table II represents the forecasting horizons. It varies from 30 minutes to 360 minutes (06 hours). The second, third and fourth columns of Table II represent the correlation coefficient (R) for training, validation and test. The fifth column of table II represents the linear correlation of the training step from each forecasting horizon.

C. ANN test step

After the training step, 30% of data are used for ANN test. Figure 4 shows an overlay of the curves from the different forecasting horizons. Each curve represents a comparative study of the measured and forecasted values over a horizon of 30, 60, 90, 120, 150, 180, 210, 240, 300 and 360 minutes respectively. Results show the steering coefficient of linear correlation lines, equal to 1 for horizons 30 to 180 minutes and 1.1 for horizons 210 to 360 minutes.

D. Reference days

Table III shows the reference days to be considered for each month. For example, June 08 is the reference day for June 2004.

The comparative study between measured and forecasted

Table III. REFERENCE DAYS ON EACH MONTH

months	June 2004	July 2004	August 2004	november 2004	December 2004
reference days	8	10	16	11	30
months	January 2005	february 2005	march 2005	April 2005	may 2005
reference days	6	25	19	7	2
months	June 2005	july 2005			
reference days	25	11			

values over the 360 horizon is presented for each reference days in Figure 5.

VI. STATISTICAL CRITERIA

The ANN statistical criteria are presented in Table IV. The first column is the forecasting horizons. The second, third, fourth, and fifth columns indicate the correlation coefficient, mean squared error, normal squared error, and statistical time, respectively. A difference of 0.026 is observed between the correlation coefficient of the 30-minute and 360-minute horizons. Figure 6 presents

Table IV. FORECASTING HORIZONS' STATISTICAL CRITERIA

forecasting horizons	R	RMSE	nRMSE	t-statistic
30	0.984	0.048	0.21	16.19
60	0.981	0.054	0.24	22.50
90	0.978	0.058	0.26	24.51
120	0.976	0.061	0.27	31.05
150	0.973	0.064	0.28	34.55
180	0.971	0.066	0.29	35.23
210	0.970	0.067	0.30	40.43
240	0.969	0.067	0.30	41.16
270	0.968	0.071	0.31	42.15
300	0.965	0.072	0.32	46.33
330	0.963	0.074	0.33	47.68
360	0.961	0.075	0.33	46.21

the correlation coefficient (R), root mean square error

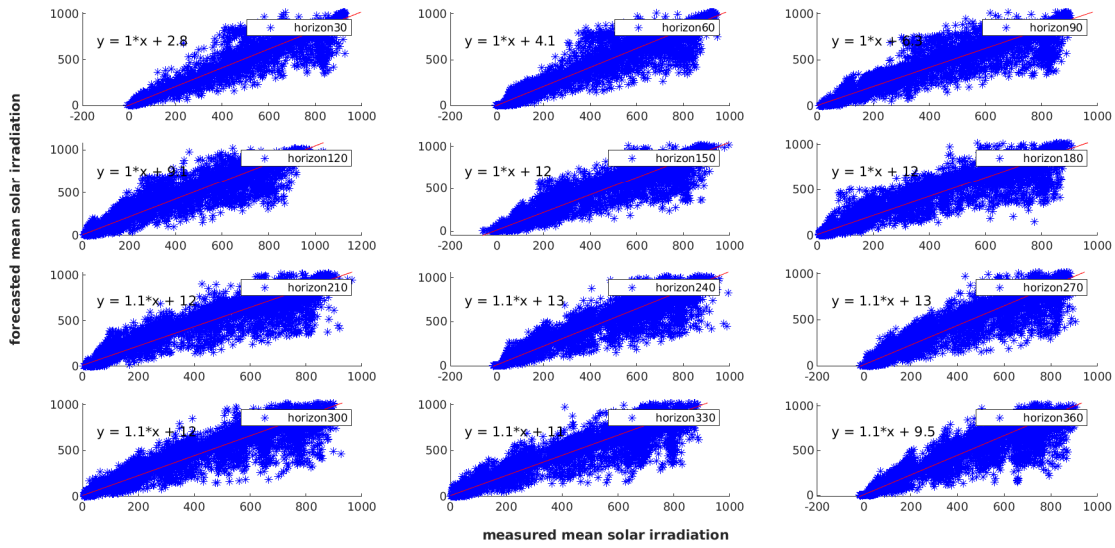


Figure 4. Solar irradiation versus the forecast horizons. Legend (blue): measured, (pink) predicted.

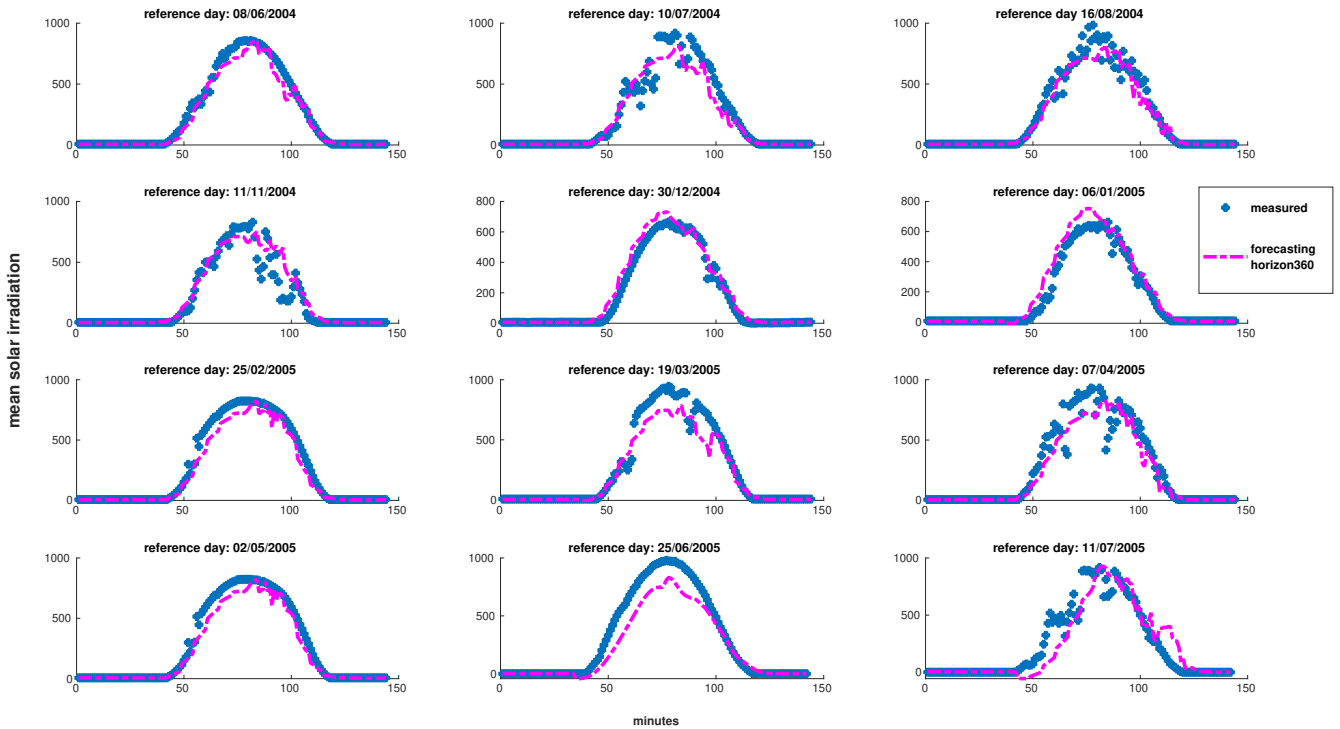


Figure 5. comparative studies between measured and forecasted values on reference days

(RMSE) and normal root mean square error (nRMSE) as a function of the forecasting horizons. There is little change in the RMSE and nRMSE as the forecasting horizon increases. The shorter the forecasting horizon,

the lower the RMSE and nRMSE. Unlike RMSE and nRMSE, correlation coefficient decreases as the forecasting horizon increases. The statistical time increases as the forecasting horizon increases.

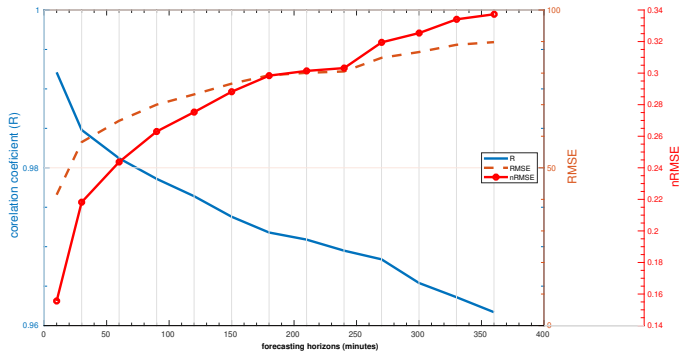


Figure 6. statistical criteria versus the forecasting horizons

## VII. CONCLUSION AND PERSPECTIVES

This work involved setting up and classifying short-term forecasting models for solar irradiation along several horizons in the north-west of Senegal. Several forecasting models are developed. The forecasting horizons are 30, 60, 90, 120, 150, 180, 210, 240, 270, 300, 330 and 360 minutes. The statistical criteria obtained allow to conclude that the solar irradiation forecasting can be extended over a six-hour horizon (360 minutes) with a correlation of 96%. These results will allow investors in solar PV power plants to reduce the investment costs often allocated to data collection equipment (reduction of a large volume of historical data saved) and will also contribute to accurate solar energy planning.

The perspectives of this paper are:

- doing the same work in the other regions of Senegal,
- forecasting solar irradiation using only temperature data.

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