PREDICTIVE CAPABILITIES OF A NARX-BASED FORECASTER USED TO PREDICT THE PV PANEL OUTPUT POWER

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Abstract*: This paper deals with the predictive capabilies of a NARX-based forecaster used to predict the output power converted with a PV panel in isolated conditions. A timeseries based NARX model is proposed and the influence of the meteorological data such as irradiance, ambient temperature and wind speed, and the impact of the training algorithm on the performance of the NARX based forecaster model is studied. The results show that for the studied area, the NARX model trained by three meteorological data as inputs, the output power as output using Bayesian Regularization algorithm gives best performance with a mean squared error of 2.10414e-2.*

NOMENCLATURE:

PV: Photovoltaic

ANN: Artificial Neural Network

NARX: Nonlinear autoregressive exogenous

$x_{normalized}$: The normalized value,

x: The actual value

x_{min}: The minimum value of each timeseries dataset

x_{max}: The maximum value from each dataset

T_C: the cell temperature (°C)

T_a: the ambient temperature (°C)

$NOCT$: the nominal operating cell temperature (°C)

$G_{g,t}$: the global irradiance on tilted surface (W/m²)

P_{PV}: is the output power from the PV panel (W)

$\eta_{PV,STC}$: the efficiency of the panel at STC conditions (%)

μ: the temperature coefficient (%/°C)

v : the wind speed (m/s)

A_{PV}: the area of the PV panel (m²)

P_{max}: The maximum power converted by the panel (W),

V_{OC}: The open circuit voltage (V)

I_{SC}: The short circuit current (A)

MSE: Mean Squared Error (W)

$P_{forcasted_i}$: the power forecasted by the NARX model (W)

P_i: the target power (W)

f : a nonlinear function

$P(t)$ and $y(t)$: Input and output of the network at time t, respectively;

n_P and n_y : the order of the imput and output, respectively.

1. INTRODUCTION

Energy is a key factor for the development of humanity. Electrical energy is the most useful form of energy, it was generated mainly from fossil fuels, and is currently mainly related to them. However, this issue has a harmful environmental effect.

Renewable energy is an alternative solution to this issue mainly in isolated areas where it is hard or impossible to connect to the grid. Among the large variety of renewable energy sources, solar energy is the most promising and the more acceptable source. Therefore, solar energy is gaining the attention of scientist, industrials and governments. However, the installation of any new project requires to know its reliability and its economic feasibility.

Since the generation of PV power is fully dependent on uncertain and uncontrollable meteorological factors, the output power of PV system changes dynamically. Therefore, a pinpoint prediction of PV power conversion is greatly difficult. The accurate forecasting of PV power production is a great challenge, that can improve the reliability of installed systems and maintain the power quality [1].

Several papers have been conducted to propose methods and techniques to forecast the energy produced PV panels. These techniques can be classified as direct and indirect forecasting techniques [1].

Nowadays the most popular techniques in direct forecasting the output power of PV installations, are the soft computing techniques based on Artificial Neural Networks (ANN) [2].

Mellit and Kalogirou outlined in [3] a comprehensive review of the use of ANNs to forecast solar energy.

Ding et all. proposed an approach based on ANN to forecast the output power of a PV system [4]. In this approach the improved back propagation learning Algorithm was adopted to overcome the shortcomings of the standard back propagation learning algorithm.

Lo Brano et all. [5] presented an approach based on different topologies of ANN to forecast the output power of PV modules. The proposed approach investigated the influence of some meteorological data without taking into account the influence of the training algorithm.

In [6], Shi et all. proposed algorithms to predict the output power of a PV system based on weather classification and support vector machine. This research investigated the influence of the weather conditions but not the training algorithm and applied to a grid connected system.

Xiao et all. [7] introduced an ANN forecaster of the output power of three technologies of PV cells. The authors of this research studied the influence of the number of hidden neurons on the prediction of the power.

The current work investigates the use of ANN for a medium-term direct forecasting of PV output power based on timeseries historical data. The main contribution in this study is to present the influence of the type of inputs and the training algorithm on the performance of the nonlinear autoregressive exogenous (NARX) model.

2. METHODOLOGY

A Multivariate times series model, based on a NARX model is proposed, to forecast the power generated by the PV panel, using three sets of meteorological data.

The different phases carried out for the current procedure are presented in *fig. 1*.

After collecting the time series dataset, a pre-processing is applied to these data. The dataset is decomposed into three sets, the first one used for the training and represent 70% of the total data, the other sets composed of 15% each are used for the test and the validation of the proposed NN.

To study the influence of the inputs on the performance of the model, different sets of data are used to train the NN.

To study the influence of the learning method on the performance of the network, three different algorithms are used for each set of the input data.

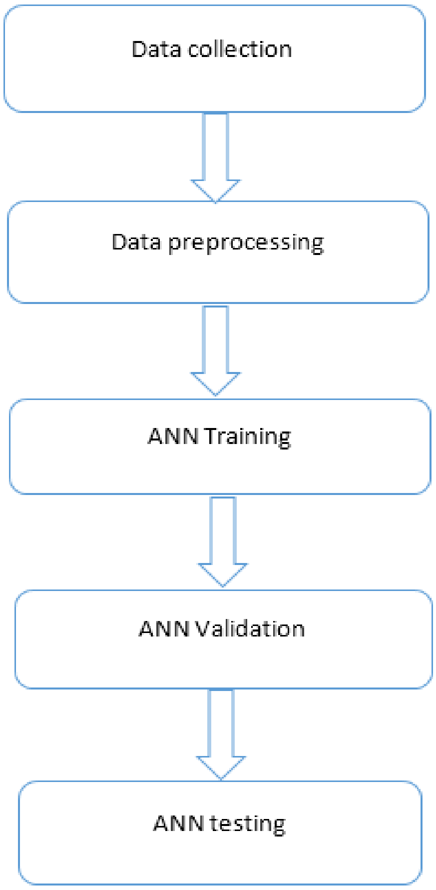

Fig. 1. Different phases of the proposed model.

2.1. Data collection

It is aimed to use the measured values of the global irradiance, the ambient temperature and the wind speed to the NN as the input data, and the values of the power converted by the PV panel as the target data, during the three phases cited above.

This data concerns one of the panels installed at the laboratory of renewable energy at the university of Skikda (Latitude= 36.848739, Longitude=6.889475).

2.2. Data pre-processing

The selected data are pre-processed as the following:

- ✓ Firstly, all the input data that leads to a target equal to zero, are deleted from the dataset.
- ✓ The other data are normalized between 0 and 1 using the following formula:

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where: $x_{normalized}$ is the normalized value, x is the actual value, x_{min} is the minimum value of each timeseries dataset, and x_{max} is the maximum value from each dataset.

2.2.1. Irradiance level

The irradiance is defined as the density of the solar radiation power received on a given surface [8]. For the present work, a 32° inclined and south oriented pyranometer is used for in-situ measurements.

The normalized data of the hourly irradiance values, for the period of the data acquisition, are presented in *fig. 2*.

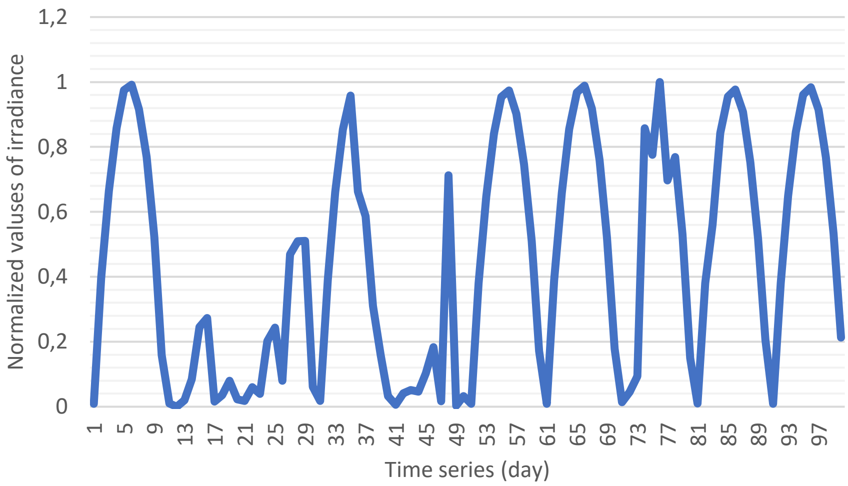

Fig. 2. Normalized irradiance values, for the period of 2 months.

2.2.2. Ambient temperature

The surface temperature of the panel has a negative impact on the PV panel performance. The power converted by the panel is reduced since the surface temperature increases. The ambient temperature has a direct impact to the panel, it is related to the PV panel surface temperature with the following equation [9]:

$$\mathrm{T_C} = \mathrm{T_a} + \frac{\mathrm{NOCT}-20}{800}\,\mathrm{G_{g,t}} \tag{2}$$

where: T_C is the cell temperature (°C); T_a is the ambient temperature (°C); $NOCT$ is the nominal operating cell temperature (°C) and $G_{g,t}$ is the global irradiance on tilted surface (W/m²).

The normalized data of the hourly ambient temperature values, for the period of the data acquisition, are presented in *fig. 3*.

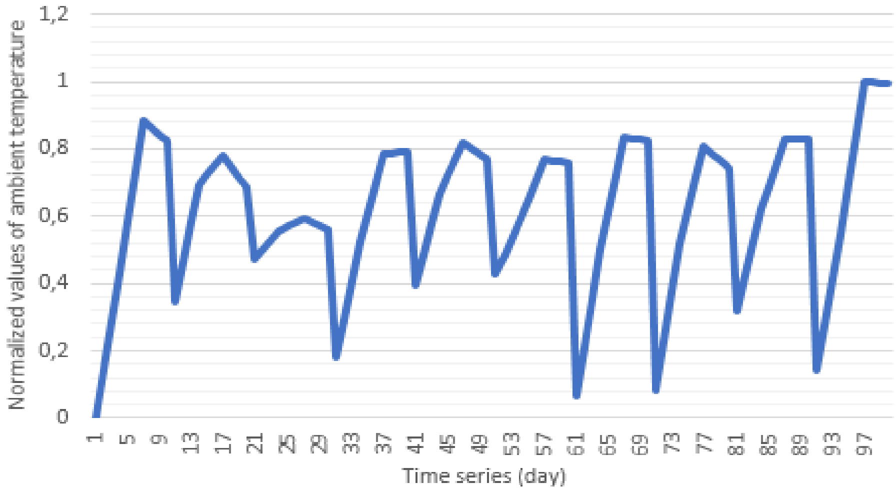

Fig. 3. Normalized ambient temperature values, for the period of 2 months

2.2.3. Wind speed

The impact of wind speed on the output power of the PV system was given by the following equation modified from [10]:

$$P_{PV} = \eta_{PV,STC}\left[\begin{array}{c} 1 + \frac{\mu}{\eta_{PV,STC}}(T_a - T_{STC}) + \\ \frac{\mu}{\eta_{PV,STC}}\frac{9.5}{5.7+3.8v}\frac{(NOCT-20)}{800}(1 - \eta_{PV,STC})G_{g,t} \end{array}\right]A_{PV}G_{g,t} \quad (3)$$

where: P_{PV} is the output power from the PV panel (W); $\eta_{PV,STC}$is the efficiency of the panel at STC conditions (%); μ is the temperature coefficient (%/°C); v is the wind speed (m/s); $A_{PV}$is the area of the PV panel (m²)

The values of wind speed used in the current study were measured for the specified area at the height of 10 m

The normalized data of the hourly wind speed values, for the period of the data acquisition, are presented in *fig. 4.*

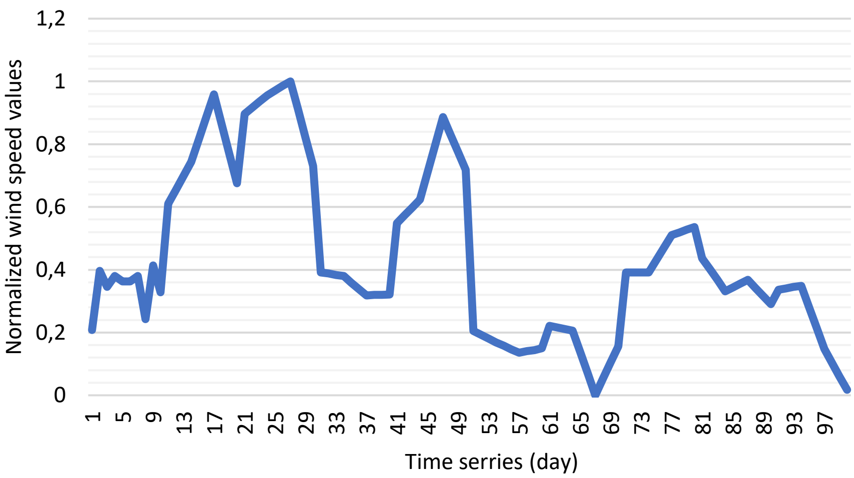

Fig. 4. Normalized wind speed values, for the period of 2 months.

2.2.4. PV panel output power

The energy converted by the PV panel is measured for a south oriented, 32° tilted monocrystalline panel (P_{max}= 235 W, V_{OC}= 30.2 V, I_{SC}=7.8 A).

The normalized data of the hourly output power values, for the period of the data acquisition, are presented in *fig. 5*.

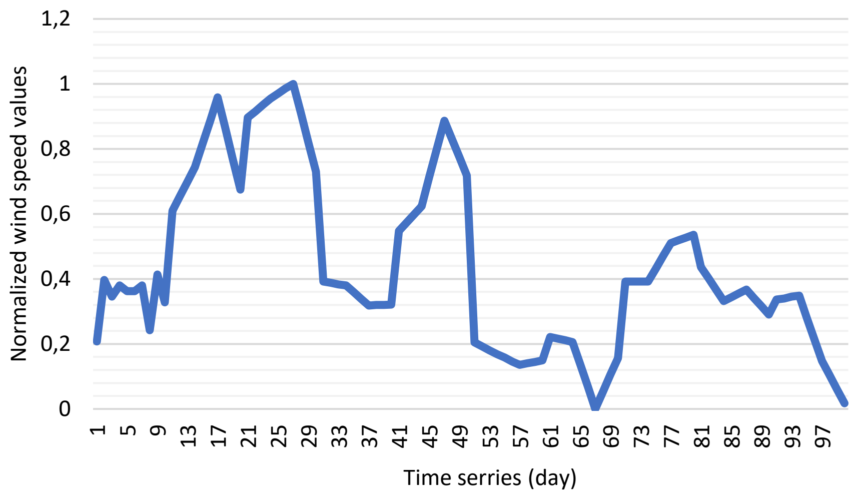

Fig.5. Normalized PV panel power output values, for the period of 2 months

2.3. ANN Architecture

For the proposed approach, we use the nonlinear autoregressive network with exogenous inputs (NARX) model to predict the output power converted by the PV panel. NARX is a recurrent dynamic NN with feedback connecting to several layers of the NN [11].

The simplest structure of the NARX model is presented in *fig. 6*.

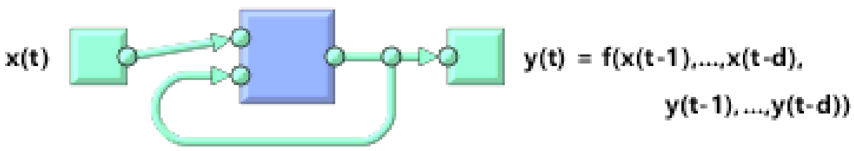

Fig. 6. General structure of NARX Network

The NARX model is mathematically formalized as [12]:

$$y(t) = f(P(t-n_P), \dots, P(t-1), P(t), y(t-n_y), \dots, y(t-1)) \tag{4}$$

where: f is a nonlinear function; $P(t)$ and $y(t)$ are, respectively, the input and output of the network at time t; n_P and n_y are the order of the imput and output, respectively.

The NARX model used is composed of input layer, one hidden layer and the output layer. The number of neurons in the hidden layer is optimized to be 10 neurons, and the number of delays is set to be 2. *Fig. 7* illustrates the NARX model proposed.

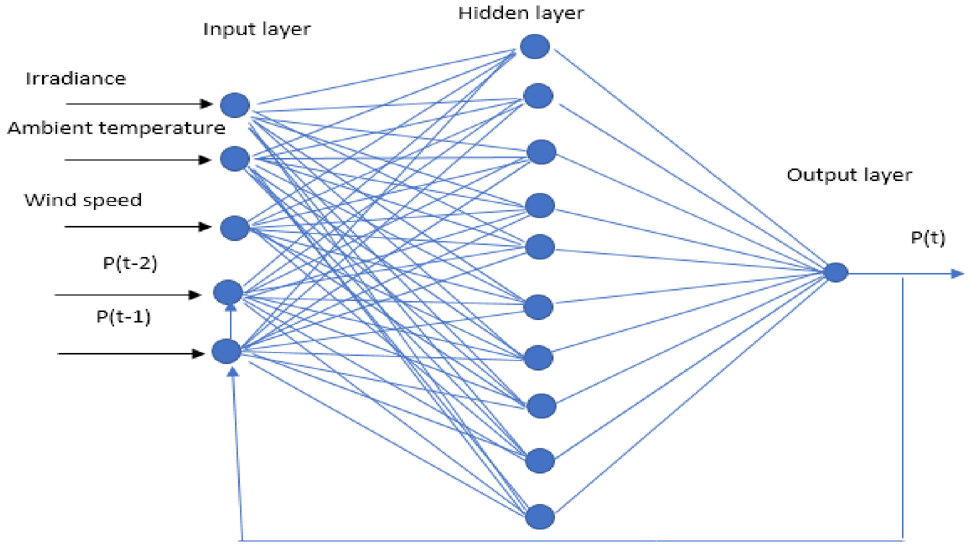

Fig. 7. Proposed NARX model structure

2.3.1. Inputs and outputs

For the present study four different sets of data are used as inputs data, where the objective is to illustrate the impact of the data on the performance of the neural network model chosen. These sets are defined as:

1. Irradiance.
2. Irradiance + ambient temperature.
3. Irradiance + wind speed.
4. Irradiance + ambient temperature + wind speed.
5. The target data is the hourly values of the PV panel output power.

2.3.2. ANN Training:

To study the influence of the training technique on the performance of the NARX model, three training algorithms are applied to each of the four cases. These are the Levenberg-Marquardt (LM), the Bayesian Regularization (BR) and the Scaled Conjugate Gradient (SCG).

2.3.3. Evaluation Criteria:

After the training and validation of the forecasting model, the accuracy of the prediction is measured by calculating the difference between the forecasted values and the target.

In this paper, the Mean Squared Error (MSE) is used to quantitatively evaluate the performance of the proposed forecasting model.

The MSE is defined as the average squared difference between the outputs of the forecasting model and the targets. It can be calculated using (5):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(P_{forcasted_i} - P_i)^2 \quad (5)$$

where: $P_{forcasted_i}$, is the power forecasted by the NARX model (W); P_i is the target power (W).

III. RESULTS AND DISCUSSIONS

The prediction model is defined and trained, to obtain the best forecasting results. The time series meteorological data consist of irradiance on inclined surface (X1), ambient temperature (X2) and wind speed (X3), taken with an hourly interval, regrouped in four datasets and used in four NARX models as follows: (Model 1 (M1): X1); (Model2 (M2): X1 + X2); (Model 3 (M3): X1 + X3); (Model 4(M4): X1 + X2 + X3). Each of the four models constructed using the previews datasets is trained by three training algorithms.

Fig. 8 presents a comparative illustration of the values of MSE calculated by the four NARX models during the testing phase.

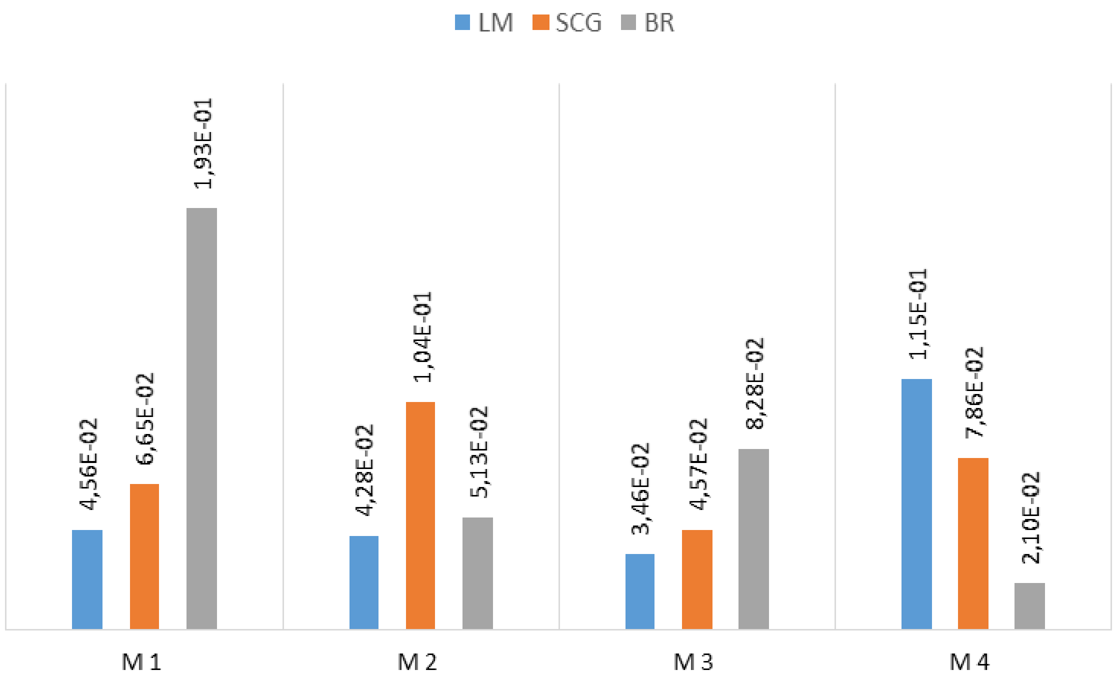

Fig. 8. Comparison between MSE for the different NARX models

From these histograms, it can be seen that the NARX model M3 gives best performance when trained using LM algorithm, and the MSE calculated with this model has the lowest value compared with other models. The model M3 presents also the best performance compared with the other models, when trained using SCG. However, the model M4 gives the best performance, when trained using BR. The MSE calculated with M4 in this case, equal to 2.10414e-2 W. It has the lowest value compared with the MSE calculated with the other models trained with the three training algorithms.

From f*ig. 8*, it can be summarized that the best forecasting of the output power converted by a PV panel, is obtained with the model M4 trained by the BR Algorithm.

IV. CONCLUSION AND PERSPECTIVES

The solar PV energy is an alternative to the traditional sources of energy, especially in remote areas. Having informative idea about the behavior of PV systems, before the installation of such system is important. An accurate prediction of the output power of a PV panel is a complicated task due to its dependence on uncertain variables. In this paper four NARX models were developed to predict the output power of a PV panel, and the performance of the models is compared in terms of the MSE values. The model used the irradiance, the ambient temperature and the wind speed, and trained using the Bayesian Regulation algorithm outperforms other models.

The future development of this work will take into consideration the following points:

- The use of more meteorological data as humidity.
- The classification of the timeseries data into several classes as clear time data, cloudy time data …
- The use of other model and techniques as the convolutional neural network.

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