Solar Radiation Estimate and Forecasting by Neural Networks-based Approach

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Abstract

This paper proposes the use of two dynamic Artificial Neural Networks (ANNs) to obtain the estimation and forecast of daily solar radiation. In particular, the Focused Time-Delay Neural Network (FTDNN) and the nonlinear autoregressive network with exogenous inputs (NARX Network) are used. The proposed models are implemented in Matlab® and experimentally validated on the basis of observed data. Both the models provided by the two considered ANNs give good performance. The NARX network gives the further advantage to allow both missing data in times series of solar radiation to be retrieved and future trend of the same quantity to be forecast.

Key words: Solar radiation, Time series predictions, Time series forecast, Artificial Neural Networks (ANN), Focused Time-Delay Neural Network (FTDNN), NARX Network

1. Introduction

Evaluation and prediction of the renewable energy is of paramount importance to achieve the optimal exploitation of the available resources and to estimate the potential production capability of power plants. This is especially beneficial in a smart grid context where prediction results can be used for energy and economical management and planning. With reference to photovoltaic (PV) generation, modeling solar radiation by means of time series forecasting techniques is then becoming more and more popular. The comparison between algorithms based on linear models and non linear models provided by artificial neural networks (ANN) has demonstrated the superiority of the latter approach to deal with problems of filling missing data and time series prediction [1-7]. In particular, Mellit et. al [1] present an overview of the AI-techniques for sizing different photovoltaic systems, showing the advantages of these methods.

In Paoli et al. [2] a focus on the prediction of global solar radiation on a horizontal plane for daily horizon is given, providing interesting information for electricity suppliers. In [3], a prediction model based on ANNs, is used to estimate monthly averaged daily global solar radiation on a horizontal surface based on weather station data; sunshine duration, maximum temperature, cloud cover and location parameters (latitude, longitude, altitude) were taken in account. In [5] an application of the MLP (Multi Layer Perceptron) neural network for the prediction of daily solar radiation data was proposed. From the comparison, in terms of the statistical indicators, with a common linear model used in literature, it is possible to note that the neural networks are more efficient and gives better results. [8] proposes the power output forecasting of PV system based on solar radiation forecasting at 24-hour-ahead by using three different NN models, i.e., FFNN, radial basis function neural network (RBFNN), and recurrent neural network (RNN); demonstrating that it is possible to forecast results by using only meteorological data in short time. Therefore, ANNs have proven to be more effective than other classical autoregressive predictors and linear models. On such a basis, this paper proposes the use of two dynamic ANNs., i.e., the Focused Time-Delay Neural Network (FTDNN) and the nonlinear autoregressive network with exogenous inputs (NARX Network), to model the daily radiation profile. Both the ANNs are tested for the estimation of the time series. Whereas only the NARX is used for radiation forecast by implementing two suitable schemes connected in cascade configuration. The advantage of this approach is the possibility to perform both the missing data filling and to obtain a forecast of radiation from a given data time series. The obtained models are experimentally validated and a comparison between them by means of suitable statistic indices is given as well.

2. Used Artificial Neural Networks

The chosen ANNs are the Focused Time-Delay Neural Network (FTDNN) and the nonlinear autoregressive network with exogenous inputs (NARX Network). They can be both classified as recurrent dynamic ANNs. The specificity of such neural networks respect to static feed-forward networks, such as Backpropagation (BP) ANN or cascade-forward ANN, is their capability to learn dynamic or time series relationships. In particular, in dynamic ANNs, the output depends not only on the current input but on the current and previous inputs, outputs or states of the network, as well. Both the networks have been trained by the Conjugate gradient backpropagation with Polak-Ribiére updates and the initial weights have been extracted randomly from a standardized normal distribution. The value of the learning rate, initially equal to 0.01, decreases according to an exponential law. The epochs used for training phase were 1000. Several network architectures, having different number of neurons in the hidden layer, have been evaluated and compared by means of statistical indices both in training and recall phases, for different values of input delays. The used ANNs with their training algorithm are implemented in Matlab® environment using the proposed functions for dynamic networks implemented for the 2012
version. In particular, a network creation function called 
timedelaynet has used to create a FTDNN.
In order to create the series-parallel NARX network the 
function narxnet was used and then the closeloop 
command to convert the previously trained network to 
parallel form [9].

A. Focused Time-Delay Neural Network
The FTDNN is a dynamic neural network, which consists 
of a feedforward network with a tapped delay line at the 
input.
This kind of neural network is well suited to time-series 
prediction. As a matter of fact, the methods used for time 
series processing have to be dynamic, i.e., they have to 
build an internal memory for a reliable temporal series 
prediction. In particular, FTDNN belongs to a general 
class of dynamic networks, called focused networks, in 
which the dynamics appear only at the input layer of a 
static multilayer feedforward network and memory is 
limited by length of tapped delay line.
The FTDNN can be trained so to perform either one-step-
ahead predictions or multistep-ahead predictions. In this 
last case the predictions are fed back to the input of the 
network, continuing to iterate.
For the application considered in this paper, the chosen 
structure of FTDNN is that shown in Fig 1. It is used to 
estimate the radiation time series in case of missing data.

B. NARX Network
An ANN that can learn dynamic or time-series 
relationships is the nonlinear autoregressive network with 
exogenous inputs (NARX). This is a recurrent dynamic 
network with feedback connections enclosing several 
layers of the network. The NARX model is well suited to 
model nonlinear dynamic systems and is commonly used 
in time-series modeling thanks to its adaptive learning 
process also with small scale meteorological data [6].
The NARX model is based on linear ARX model. It can 
be mathematically represented as:

\[ y(t) = f(y(t - 1), \ldots, y(t - n_y), u(t - 1), \ldots, u(t - n_u)) + \epsilon(t) \]  

where \( y(t) \) and \( u(t) \) are the output and the input of the 
model at a discrete time step \( t \), respectively, whereas \( n_y \geq 1, n_u \geq 1, n_u \leq n_y \) are the input-memory and output memory 
orders and \( \epsilon(t) \) is a noise term, usually assumed Gaussian 
and white.
In this network the next value of the dependent output 
signal \( y(t) \) is regressed on previous values of the output 
signal and previous values of an independent (exogenous) 
input signal. A feed-forward neural network, such as a

standard Multilayer Perceptron (MLP), can be used to 
approximate the nonlinear mapping function \( f \).
In this paper, the NARX network, where the exogenous input 
is the temperature, has been implemented using two 
configurations: a series-parallel architecture for training the 
network to model the daily solar radiation behavior and a 
parallel architecture to perform the forecast of the daily solar 
radiation (Multi-step ahead prediction). These configurations 
are illustrated in Fig 2.
It should be noted that the first configuration is used with the 
same aim of the FTDNN, say to estimate the radiation profile 
in case of missing data. The second configuration is used, in 
cascade with the first, to perform the radiation forecast.

\[ x_{n+1} = x_n + \alpha_n \Delta x_n \]  

where, given a function \( f(x) \) of \( N \) variables to be 
minimized, \( \Delta x = -\nabla_x f(x) \) indicates the direction of 
maximum increase, i.e. the search direction. The parameter 
\( \alpha(k) \) is selected to minimize the performance along the 
search direction.
So, the first search direction is the opposite of the gradient of 
performance:
\[ s_n = \Delta x_n = -\nabla_{x_n} (f(x_n)) \]  
\[ (3) \]

In subsequent iterations the search direction is computed from the new gradient and the previous search direction, according to the formula:

\[ s_n = \Delta x_n + \beta_n s_{n-1} \quad (n \geq 1) \]  
\[ (4) \]

The parameter \( \beta_n \) can be computed in several different ways. For the Polak-Ribière variation of conjugate gradient it is computed according to:

\[ \beta_n^{PR} = \frac{\Delta x_n^T (\Delta x_n - \Delta x_{n-1})}{\Delta x_{n-1}^T \Delta x_{n-1}} \]  
\[ (5) \]

4. Research context and used data

This study has been carried out for the largest island in the Mediterranean Sea: Sicily, Italy, which extends over an area of 25,700 km². Considering the average conditions of the entire region, Sicily can be defined as a region with a wet-mild climate or in other words, mesotermic-wet subtropical climate, with a dry summer, i.e. the typical weather of the Mediterranean area, with an average temperature in the hottest month greater than 22 °C and with a precipitation regime more intense in the coldest season. The average annual temperature varies between 11°C and 20°C, depending on the considered zone. Concerning the solar radiation, in Sicily region the mean annual solar radiation is equal to 5,4 kWh/m²/day: the most high in Italy.

Figure 3 shows Digital Elevation Model (DEM) of the entire Sicily having a horizontal resolution of 100 m. It can be observed that about 62% of the surface is characterized by a hilly morphology, whereas about 24% can be ascribed to a mountainous morphology and the remaining part to plains. The most extended plain is the one around Catania in the Eastern part, whereas the Mount Etna with its 3,323 m is the highest mountain of Sicily. Along the Northern coast, from East to West, are situated the Peloritani, Nebrodi and Madonie Mountains, some of their peaks reaching 2,000 m. A series of high plateaus, which constitute Hyblaean Plateau, characterize South-Eastern part of Sicily [10].

The dataset used is the daily solar radiation and the daily mean temperature recorded during 3 years (2010-2012) in Palermo (38°6'43"56 N, 13°20'11"76 E), in the north-west of Sicily (red dot in Fig. 3). These data were provided by SIAS (Servizio Informativo Agrometeorologico Siciliano). Data give, for the considered period of time, a complete series of daily solar radiation.

In order to make the Neural Network training more efficient, a preprocessing procedure was applied to temperature and solar radiation data. In particular, a normalization step is applied to both the input vectors and the target vectors in the data set and the network output was reverse-transformed back into the units of the original target data (post-processing procedure).

5. Results

The indices selected to measure the performance of the neural networks are the Normalised Root Mean Squared Error (nRMSE), and the Coefficient of Variation of the Root Mean Squared Error (CV-RMSE). They are defined, respectively as:

\[ \text{nRMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [Y_i - \hat{Y}_i]^2} \]  
\[ (6) \]

\[ \text{CV(RMSE)} = \frac{1}{\bar{Y}} \sqrt{\frac{1}{N} \sum_{i=1}^{N} [Y_i - \bar{Y}]^2} \]  
\[ (7) \]

Where \( Y \) is the original time series, \( \hat{Y} \) is the predicted time series, \( Y_{\text{max}}, Y_{\text{min}} \) are the maximum and minimum observed values and \( \bar{Y} \) is the mean of the observed values.

The choice of a criterion as measure of the performance is an important issue. In particular it is crucial that the results are totally independent on the used scale of variables. For this reason in this study the chosen indices are normalised.

Table 1 gives the values of nRMSE and CV both in the training phase (nRMSEt, CVt) and in the recalling phase (nRMSEr, CVr) for FDTNN and Table 2 shows the same indices for the case of the NARX network. The best network is that where the minimum deviation between indices in the two phases is observed. In particular, the best performance are obtained by the MLP 1-3-1 with delay equal to 4 for FDTNN and by the MLP 2-3-1 with delay equal to 4 for NARX.

The comparison between measured (original targets) and estimated (network predicted) data with FTDNN is shown in Fig. 4. In Fig. 5 the performance of the NARX network-based is shown, for the application with series-parallel structure (Fig. 2, upper). As previously said, in this configuration the NARX network performs the estimation of radiation data. The comparison between the observed data and those estimated by NARX in Fig.5 refers to the network with the parameters that have provided the best performance from the comparison of the indices in Table 2 (2-3-1, delay=4).
Table 1. Assessment of the FTDNN-based model

<table>
<thead>
<tr>
<th>ANN</th>
<th>Delay</th>
<th>nRMSEf</th>
<th>nRMSEEf</th>
<th>CVf</th>
<th>CVt</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-3-1</td>
<td>2</td>
<td>0.17</td>
<td>0.14</td>
<td>0.31</td>
<td>0.25</td>
</tr>
<tr>
<td>1-3-1</td>
<td>4</td>
<td>0.15</td>
<td>0.16</td>
<td>0.27</td>
<td>0.27</td>
</tr>
<tr>
<td>1-3-1</td>
<td>6</td>
<td>0.13</td>
<td>0.18</td>
<td>0.25</td>
<td>0.31</td>
</tr>
<tr>
<td>1-3-1</td>
<td>8</td>
<td>0.13</td>
<td>0.17</td>
<td>0.24</td>
<td>0.29</td>
</tr>
<tr>
<td>1-5-1</td>
<td>2</td>
<td>0.17</td>
<td>0.14</td>
<td>0.31</td>
<td>0.25</td>
</tr>
<tr>
<td>1-5-1</td>
<td>4</td>
<td>0.15</td>
<td>0.15</td>
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<tr>
<td>1-5-1</td>
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<td>0.13</td>
<td>0.16</td>
<td>0.24</td>
<td>0.27</td>
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<tr>
<td>1-5-1</td>
<td>8</td>
<td>0.11</td>
<td>0.19</td>
<td>0.20</td>
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<td>1-10-1</td>
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<td>0.16</td>
<td>0.15</td>
<td>0.30</td>
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<tr>
<td>1-10-1</td>
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<td>0.19</td>
<td>0.24</td>
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<tr>
<td>1-10-1</td>
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<td>0.10</td>
<td>0.17</td>
<td>0.19</td>
<td>0.30</td>
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<tr>
<td>1-10-1</td>
<td>8</td>
<td>0.10</td>
<td>0.19</td>
<td>0.18</td>
<td>0.34</td>
</tr>
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Table 2. Assessment of the NARXnet-based model

<table>
<thead>
<tr>
<th>ANN</th>
<th>Delay</th>
<th>nRMSEf</th>
<th>nRMSEEf</th>
<th>CVf</th>
<th>CVt</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-3-1</td>
<td>2</td>
<td>0.14</td>
<td>0.20</td>
<td>0.24</td>
<td>0.36</td>
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<tr>
<td>2-3-1</td>
<td>4</td>
<td>0.13</td>
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<td>0.35</td>
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<tr>
<td>2-3-1</td>
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<td>0.20</td>
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<td>0.36</td>
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<tr>
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<td>0.23</td>
<td>0.22</td>
<td>0.39</td>
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<tr>
<td>2-5-1</td>
<td>6</td>
<td>0.13</td>
<td>0.22</td>
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<tr>
<td>2-5-1</td>
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<tr>
<td>2-10-1</td>
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<td>0.24</td>
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<td>2-10-1</td>
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<td>0.21</td>
<td>0.22</td>
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<tr>
<td>2-10-1</td>
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<td>0.12</td>
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<td>0.21</td>
<td>0.39</td>
</tr>
<tr>
<td>2-10-1</td>
<td>8</td>
<td>0.13</td>
<td>0.22</td>
<td>0.23</td>
<td>0.40</td>
</tr>
</tbody>
</table>

It is possible to observe that both the chosen dynamic ANNs give a good estimation of the radiation data. In particular, the FTDNN has a simpler structure then it is easier to be implemented and require a lower computational burden.

On the other hand the NARX network exploits more information then it is suitable to carry out both time series estimation and forecast, as it will be shown in the following.

For forecast purpose the NARX network has been trained using all the available (three years) daily data of temperature and solar radiation.

From these two data sets one hundred days to the end of the third year have been removed to simulate a time series affected by missing data. Then the structure and parameters of the network have been chosen and the series-parallel configuration was used (Fig. 2, upper). Once trained the NARX, the command closeloop of Matlab® is used and a multi-step ahead prediction for the fictitious period of missing data is obtained by means of the parallel configuration (Fig. 2, lower).

Fig 6 shows the comparison between the observed daily solar radiation and the predicted one in forecasting phase.

6 Application to the PV Energy prediction

In order to verify the validity of the proposed models for the prediction of the energy generated by a PV field, an actual experimental installation has been considered as a benchmark.

The chosen PV plant is a 2.9 kWp PV plant, installed on a roof footbridge at the University of Palermo – Faculty of Engineering [11]. The PV plant is composed by two 1.45 kWp sub-arrays, that can work independently each other. For the purposes of this work only a sub-array has been considered.

The electrical features of each sub-array under standard test conditions (stc: $G_{stc}=1000W/m^2$, $T_{stc}=25^\circ C$) are the following:

- Open circuit voltage ($V_{oc}$): 228.6V;
- Short – circuit current ($I_{sc}$): 9.2A;
- Maximum power voltage ($V_{mp}$): 186V;
- Maximum power current ($I_{mp}$): 8A.

Assuming that, for given temperature, the generated energy is nearly proportional to solar radiation, and that the plant is...
always operated at the maximum power point, the produced energy at the N-th day has been calculated according to (8) using both observed and estimated radiation data.

\[ E(N) = \frac{1}{G_{stc}} (V_{mp} I_{mp})_{stc} \sum_{i}^{N} W_i \]  

(8)

where \( W_i \) is the i-th observed (estimated) daily solar radiation value and \( (V_{mp} I_{mp})_{stc} \) is the power generated by the plant under standard test conditions.

Fig. 7 shows the comparison of energy calculated on the basis of observed data and on the basis of data estimated by FTDNN model in a period of one year. Fig. 8 shows the comparison of energy calculated on the basis of observed data and on the basis of data estimated by NARX model in a period of one year. In both cases a very good prediction of energy generated by the PV array is obtained. However the absolute error on estimated energy is lower in the case of NARX model, as shown in Fig. 9.

Fig. 7 PV Energy calculated on the basis of observed data (red) and on the basis of data estimated by FTDNN model (blue).

Fig. 8 PV Energy calculated on the basis of observed data (red) and on the basis of data estimated by NARX model (blue).

7 Conclusions

In this paper the use of two dynamic ANNs (FTDNN and NARX) to obtain the estimation and forecast of daily solar radiation is proposed. With the followed approach it is possible to achieve a complete set of data even in case of sensors faults or maintenance. Moreover, by exploiting forecast features, energy management is easier especially when storage systems are adopted. By the presented experimental validation it is possible to conclude that both the models provided by the two considered ANNs give good performance. The NARX network gives the further advantage to allow both missing data in times series of solar radiation to be retrieved and future trend of the same quantity to be forecast.

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