A New Neural Networks Approach Used to Improve Wind Speed Time Series Forecasting

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ABSTRACT

Generally, wind turbines convert the energy of wind into electricity. In this order, it is essential to predict accurately this source's availability and intensity at the same location and height where wind electric generators will be installed, and therefore obtain reliable time-series data. The problem of meteorological time series prediction can be formulated as a system identification problem. To improve the prediction of these meteorological time series, we describe then use an application of a new neural networks approach in this paper. This novel, robust, and reliable forecasting method is based on the application of a new learning algorithm that allows a renewal of learning data, with time. For our algorithm a neural network is developed to estimate just one value *y (t+1)*, then it is taken up with a new learning set enriched by data freshly measured. The obtained results showed a good agreement between measured and predicted series, and the mean relative error over the whole data set, which are not exceeding 5 %.

I. Introduction

Depletion of fossil energy resources on a global scale and with environmental problems accelerated the development and the use of alternative resources mainly based on renewable energy resources. These energy resources give a promising solution to answer the growing energy demand because they are available, inexhaustible, and their conversion processes are non-polluting [1]. However, the performance of renewable energy systems (RES) is directly correlated to weather conditions to the area of their installation, as well to meteorological data such as solar radiation, ambient temperature, and wind speed. The prediction of these data has a very important role particularly in: human plans for daily activities, agricultural activities and irrigation, architectural design of buildings and infrastructures, and the optimization and sizing of renewable energy systems [2]. One of these RES is wind energy that is fastly growing in the world [3]; this technology as all technologies of renewable energy field requires the use of precise meteorological data during the optimization process. It is therefore essential to be able to formulate forecasting and estimation models for these meteorological data [4].

To resolve the problem of estimating wind speed values and obtain reliable wind time series that can be used in the optimization of wind energy systems many models were developed [5]. Most of the previous works on wind speed prediction (WSP) were performed using physical or numerical mathematical models [6]. However, no model gives a perfect solution to the WSP. Face to these disadvantages few software prediction models have been developed to make WSP more accurate such as artificial neural network (ANN), fuzzy logic, and neuro-fuzzy [7]. Referring to the prediction of parameters it is well known that ANNs represent a valuable tool for this kind of analysis [8], [9]. They are specifically useful when it is necessary to build a model from a set of existing meausured data, or to simulate the behavior of systems characterized by noisy and incomplete data [10]. For which many examples are existing [10]. As time-series prediction is conventionally performed entirely by inference of future behavior from examples of past behavior, it is a suitable application for an ANN predictor.

Different models based on the neural networks were introduced in the literature for predicting meteorological data [11], [12], [13], [14], [15]. Different models of neural networks have been studied and compared in [15]. However, there will always be inherent and irreducible uncertainty in every prediction. This epistemic uncertainty corresponds to the incomplete knowledge of the processes that influence future events. Therefore, in complement to point forecasts of meteorological time series, a major importance is to provide means for assessing online the accuracy of these predictions. Therefore, the research efforts still focus on a significant decrease in the level of prediction error. A review on the subject has allowed us to reach the limitations in this research [16] and it is the problem that we are mainly interested in. For this reason, this paper focus on the developpement of new neural network approach for wind speed prediction. This method have shown best performances.

II. Methodology

The accuracy of Artificial Neural Networks forecast depends on the training data and not on any physical relation, different inputs directly influence forecast accuracy. The problem of time series prediction is formulated as a system identification problem, where the input of the system is the past values (*y (t - 1), y (t - 2), y (t - 3), …*) of a time series and its desired output (*y (t), y (t + 1), y (t + 2), …*) are the future of a time series.

To bridge that gap we have introduced (developed) a new algorithm of learning for neural networks. This new method allows a renewal of learning data with time:

So to predict y_n we use $Y_{n-1}, Y_{n-2}, Y_{n-3} \ldots\ldots Y_1$ as learning data,

and to predict y_{n+1} we use $Y_n, Y_{n-1}, Y_{n-2}, Y_{n-3} \ldots\ldots Y_2$ as learning data.

$Y_{n+1}, Y_n, Y_{n-1}, Y_n\ Y_{n-2}, Y_{n-3} \ldots\ldots Y_3$ will be learning data to predict y_{n+2}.

y : is the predicted energy output.

Y : Vector of inputs.

Therefore, the artificial neural network that allowed the calculation of y_n is different from the one that is used to calculate y_{n+1}. The difference lies only in the weights values (synaptic weights), because it keeps the same ANN architecture (a two-hidden layer neural network) the same number of neurons per layer and the same activation functions. It also maintains all the characteristics of learning.

Neural network

A neural network is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two aspects:

- The network through a learning process acquires knowledge.
- Interconnection strengths known as synaptic weights are used to store the knowledge.

Learning is a process by which the free parameters (synaptic weights and bias levels) of a neural network are adapted through a continuing process of stimulation by the environment in which the network is embedded. The type of learning is determined by how the parameter changes take place. In a general sense, the learning process may be classified as supervised learning and as unsupervised learning. In what follows, there is a detail about the used neural network type, and the algorithm chosen to be used in the learning process.

a) Multilayer Percepteron

A multilayer perceptron (MLP) has an input layer of source nodes and an output layer of neurons (computation nodes); these two layers connect the network to the outside world. In addition to these two layers, the multilayer perceptron usually has one or more layers of hidden neurons, which are so-called because these neurons are not directly accessible. The hidden neurons, extract important features contained in the input data.

The architecture used in this work is a network with one input neuron, representing the hourly average wind speed, two hidden layers, each containing three neurons. Finally, the network has one output layer with one neuron, representing the predicted wind speed. The neural architecture is characterized by the hyperbolic tangent transfer function in the first hidden layer and the linear transfer function in the second hidden layer, in combination with a backpropagation learning algorithm.

In the remainder of the paper, the neural network described in this section is called by (MLPu).

b) The training algorithm

Backpropagation is the network training method of choice for many neural network projects and for good reason. Like other weak methods, it is simple to implement, faster than many other "general" approaches, well-tested by the field, and easy to mold (with domain knowledge encoded in the learning environment) into very specific and efficient algorithms.

Several algorithms are found in the literature; in this work, we have used the Levenberg-Marquardt (LM) backpropagation algorithms. The gradient methods are the most used to adjust the parameters of the MLP neural networks (weight). These algorithms are based on the minimization of a derivable cost function. Usually, this function is defined as follows [16]:

$$j(\theta) = \frac{1}{2}\sum_{i=1}^{N}(y_t - \hat{y}_t)^2 \tag{1}$$

Where y_t is the original time series data, $\hat{y}_t$ is the computed data.

The gradient of the cost function $J(\theta)$ is given by:

$$\nabla j = \begin{pmatrix} \frac{\partial j}{\partial \theta_1} \\ \vdots \\ \vdots \\ \frac{\partial j}{\partial \theta_M} \end{pmatrix} \tag{2}$$

Where M is the number of unknown parameters.

The algorithm of Levenberg-Marquardt rests on the application of the formula of the parameters update defined as follow [17]:

$$\theta^K = \theta^{K-1} \pm \left[H(\theta^{k-1}) + \mu_k I\right]^{-1} \nabla j(\theta^{k-1}) \tag{3}$$

Where $H(\theta^{K-1})$ the Hessian of the cost is function and μ_K is the step.

Mathematical example

In Figure 1 and 2 the target function was:

$$T = \sin(x) + \sin(2 * y) \tag{4}$$

With $y=0$ if $x<25$ rad.

This example is constructed in a way that the variable y does not change state during the learning phase but we activate the variable y during the validation

In Figure 1, during the learning rate the input named 'y' was constant, so the networks cannot follow the changes that arise in this variable during the validation. The neural network cannot monitor the changes.

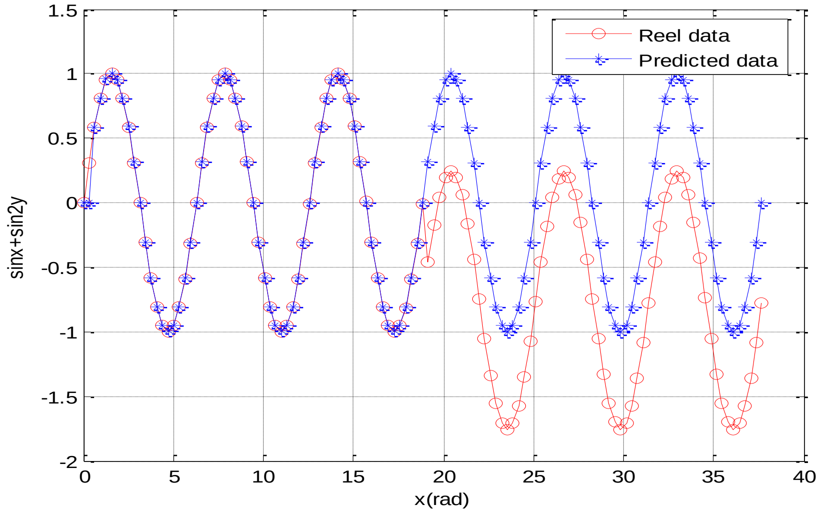

Figure 1. Comparison between the two outputs: obtained and desired with period of learning from *0* to *10* rad as learning data.

In Figure 2 we opt for dynamic learning (our approach described in part II). We observe that the ANN loses control during one-step then found a very good accuracy; this is due to dynamic learning. Therefore, we can clearly note that our approach allows predicting hidden variables. These properties give it a better prediction accuracy.

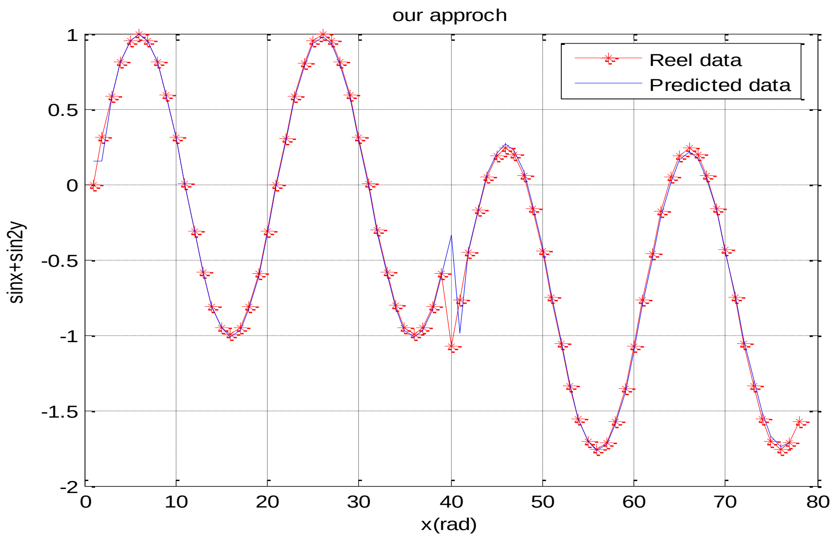

Figure 2. Comparison between the two outputs: obtained and desired with period of learning of 10rad as learning data for our approach.

III. Results and discussion

The tool used for the creation, manipulation, and visualization of the results obtained by the networks of neurons is Matlab, version 7. the performances of a multi-layer perceptron MLP (with one input neurons, two-hidden layers, each containing three neurons and one output layer) in combination with a backpropagation dynamic learning (our approach), was comprehensively investigated for forecast value of next hourly average wind speed in figure 3.

The structural development of the neural network is described in the literature [18].

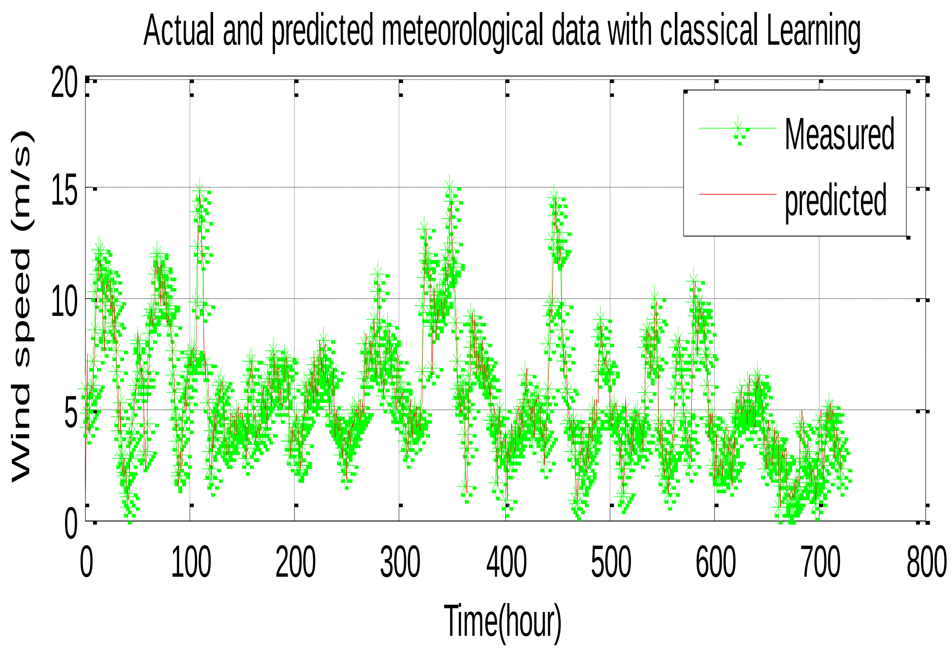

Figure 3. Actual and predicted wind speed data with our approach.

Figure 3 shows a slight shift between measured and predicted values of one hour (on average) because the predicted value tends to follow the last hour value given. The mean relative error, for the entire test, is 3% and the root mean squared error (RMSE) is 0.1840 m/s. These results prove the effictiveness of the developed approach.

IV. Conclusion

Prediction meteorological data plays a very important role in the design of renewable energy systems, âparticularly in wind topic. The problem of time series prediction is formulated as a system identification problem, where the input of the system is the past values (*y (t - 1), y (t - 2), y (t - 3), …*) of a time series and its desired output (*y (t), y (t + 1), y (t + 2), …*) are the future of a time series.

In this work, due to the strong intermittence characterizes fluctuations in wind speed, we have studied various time series of wind speed in the surface layer and discussed the intermittent nature of the time variations of wind. Recall that they are strongly non-Gaussian. These statistical properties of the wind suggest the use of a model based on neural networks.

Artificial neural networks associated with intermittent processes by evolutionary learning have a strong ability in the construction of a new stochastic model of wind speed. This approach gives a good solution in meteorological time series prediction due to the faithful reproduction of this stochastic character of wind, where the mean relative error over the whole data set is not exceeding 5 %.

Nomenclature

RES: Renewable Energy Systems
WSP: Wind Speed Prediction
ANN: Artificial Neural Network
MLP: Multi Layer Perceptron
LM: Levenberg-Marquardt
RMSE: Root Mean Squared Error

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