COMPARISON OF TECHNIQUES AND INPUT DATA FOR NEURAL NETWORKS IN PREDICTION OF WIND SPEED

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1. Introduction

In recent years, renewable energy sources have gained importance worldwide and became one of the most important sources to supply the electrical energy demand. Wind energy have been highlighted as one of the cleanest technologies, showing wide applicability. In the Brazilian state of Ceará there was in the last years an investment of about 644 million euros in the construction of 250 towers for wind energy production, which are distributed in 14 parks. The total electrical output of these wind parks is 500 MW. Ceará is the Brazilian state with the highest installed wind power but this represents only 5% of the state wind potential. The installation and operation of a wind farm needs a planning that requires forecasts of wind speeds in order to get an estimation of the plant generation capacity. Application of Artificial Neural Networks (ANN) to forecast wind has proved a convenient and efficient technique. In this way, the present paper has as main goal the use of ANN to make wind speed forecasts based on meteorological data measurements as input. Additionally, the paper compares the results of applying different ANN methodologies available to estimate the wind potential, as well as the effect of different input data and the combination of the data (wind speed, ambient temperature, air humidity and time of the measurement) to forecast the wind speed.The remainder of the paper is organized having s2 review, section 3 presenting the ANN models, section 4 the methodology, section 5 the training results, ending with the conclusion in section 6.

2. Review

The growing demand for electric power is a challenge for the countries to explore all the possibilities of generation. Wind power is appointed as one of the most clean and emission free of the sources available today. Improvements have been applied to make this source the first option as a complementary source of energy connected to the grid. But wind power has certain characteristics that cause difficulties to a larger use, such as the intermittence. To overcome this barrier, forecasting methods are applied.

Accurate wind speed forecasts contribute to reduce the reserve capacity needed for operating wind turbines connected to the grid. In this way, stops can be scheduled reducing the costs of maintenance and refining operational plans. According to (A. A. Khan , 2009), Pravin B. Dangar et al (2010) and A. Agüera et al (2009), wind forecast is a complex task due to the many influences of the meteorological parameters involved. So, a variety of approaches and techniques have been proposed.

According to (Gong Li, Jing Shi, 2010), the Artificial Neural Network (ANN) is being widely utilized in different fields including transient detection, pattern recognition, approximation and time series forecast. According to (Anurag More, M.C. Deo, 2003), ANN has been utilized for its superior performance compared with traditional forecast methods. (T. Ichikawa, K. Ichiyanagi, 2010) also applies ANN to forecast solar energy and wind speeds in a time series approach. (T.G. Barbounis, J.B. Theocharis, 2005) showed that specially Recurrent Neural Networks allow for temporal information to be represented and manipulated several variations of ANN are available and the performance for wind speed forecast vary the same way.

The present paper compares some ANN schemes to predict wind speed based on meteorological data. Wind speed, ambient temperature and air humidity are considered as input. The data are from FUNCEME (Ceará's Water Resource and Meteorological Foundation), which has 76 weather stations in this Brazilian state, according to figure 1. The stations supply on-line measurements of wind speed and direction at a height of 10 meters, ambient temperature, air humidity, solar radiation, precipitation and pressure at intervals of 3 hours.

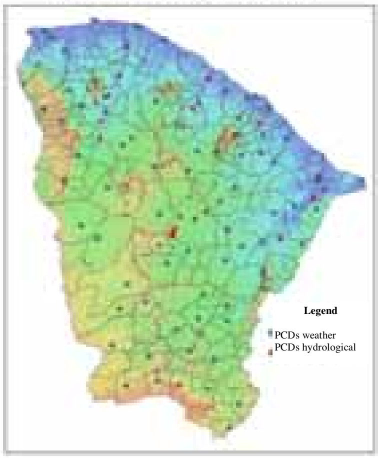

Fig. 1: FUNCEME meteorological stations

The Catarina city (06 ° 07 '51 "S 39 ° 52' 40" O) figure 2, climate tropical semi-arid hot, altitude 580 meters above sea level, has one of these stations and was chosen due to the greater data reliability. This work also compares the effects of different input data or the combination of them to estimate the wind potential.

Fig. 2: Catarina city

3. Neural network models

Time series forecasting is the use of a model to forecast future events based on known past events to predict data points before they are measured.Among the techniques used for forecasting time series, are those based on different architectures of ANN such as Elman (ELM), layered-recurrent network (LRN), Feedforward input-delay backpropagation network (FFTD) and distributed time delay neural network (DTDNN). Howard et al. (2008) explain that ANN can be classified into dynamic and static categories. Static (feedforward) networks have no feedback elements and contain no delays; the output is calculated directly from the input through feedforward connections. In dynamic networks, the output depends not only of the current input, but also of the current or previous inputs, outputs or states of the network. Dynamic networks can also be divided into two categories: those that have only feedforward connections, and those that have feedback or recurrent connections. Networks with dynamic features are well applied to time series, which is the focus of the present study.

3.1. Elman backpropagation network (ELM)

According to Howard et al. (2008), the Elman network commonly is a two-layer network with feedback from the first-layer output to the first-layer input. This recurrent connection allows the Elman network to detect and generate time-varying patterns. A two-layer Elman network is shown in figure 3.

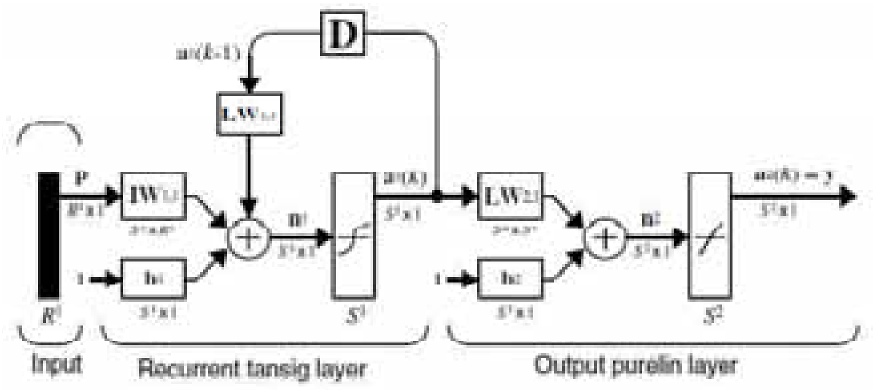

Fig. 3: ELM

3.*2. Layered-recurrent network (LRN)*

In the LRN there is a feedback loop, with a single delay, around each layer of the network except for the last layer. The original Elman network has only two layers and uses a tansig transfer function for the hidden layer and a purelin transfer function for the output layer. The original Elman network is trained using an approximation to the backpropagation algorithm. The newlrn command generalizes the Elman network to have an arbitrary number of layers and to have arbitrary transfer functions in each layer. The toolbox trains the LRN using exact versions of the gradient-based "Backpropagation." Figure 4 illustrates a two-layer LRN.

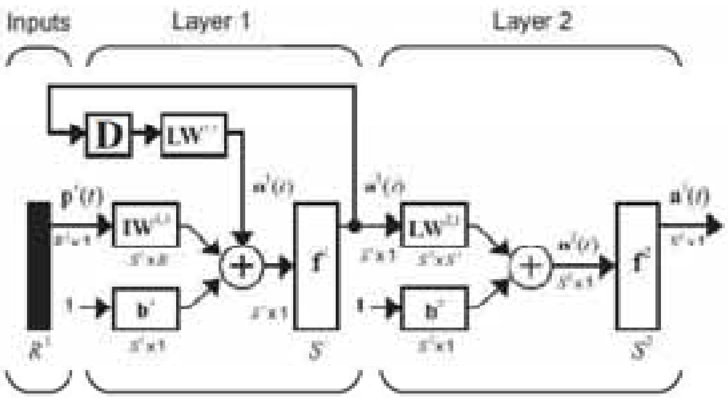

Fig. 4: LRN

3.3 Feedforward input-delay backpropagation network (FFTD)

FFTD is the most straightforward dynamic network, which consists of a feedforward network with a tapped delay line at the input. In Matlab, this network is named as Feedforward input-delay backpropagation network (FFTD), but it is also called focused time-delay neural network (FTDNN). This is part of 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. Figure 5 illustrates a two-layer FTDNN.

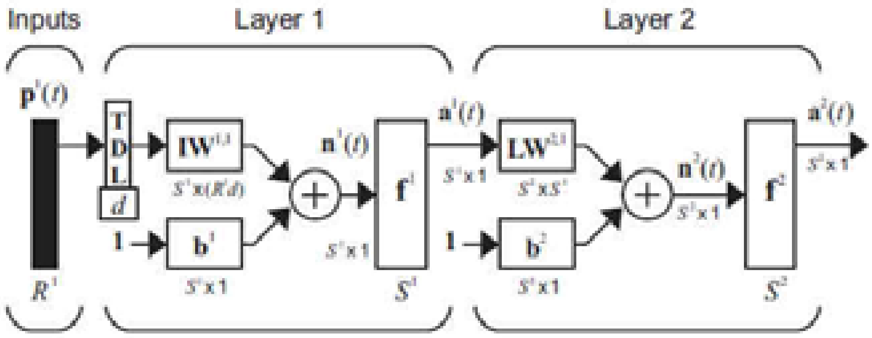

Fig. 5: FTDNN

3.4. Distributed time delay neural network (DTDNN)

The FTDNN has the tapped delay line memory only at the input to the first layer of the static feedforward network. In the DTDNN there is a distribution of the tapped delay lines throughout the network. The distributed TDNN was first introduced for phoneme recognition. The original architecture was very specialized for that particular problem. Figure 6 shows a general two-layer distributed DTDNN.

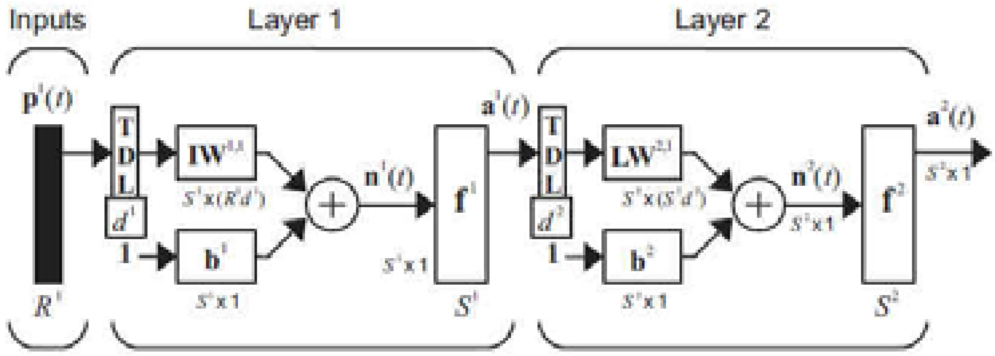

Fig. 6: DTDNN

4. Methodology

According to (Gong Li, Jing Shi, 2010), different network structures, learning rates and inputs are believed to result in different forecast accuracies. A comprehensive investigation is needed in selecting the type of ANN training window size, number of hidden layer neurons, evaluation criteria and different input data. In the present paper the evaluation criteria was the Mean Absolute Percent Error (MAPE):

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|A_{t-}F_t\,|}{A_t} \qquad \text{(eq.1)}$$

Where N is the number of points analyzed, At is the actual value and Ft is the predicted value. For all ANN applied, the stopping criterion was the maximal number of iterations of 600 training epochs.

For the present paper, initial trainings were performed with 3 years of input data. The first results showed MAPE values of around 32 to 40%. Xingpei LI et al. (2009) used a 10 days period for the ANN training; so, it was considered in the present study an investigation of a 1 to 30 days training period to find better MAPE values. 2 groups of simulations with different input data were used; in the Group 1 (only the wind speed as input data), all networks have 4 inputs and 1 output (the inputs are a sequence of 4 wind speed data, taken every 3 hours), having as target the next wind speed data. Group 2 has as input wind speed, ambient temperature, air humidity, day, hour and month. For groups 1 and 2 four ANN techniques were applied. For group 2 all networks have 15 inputs and 1 output (15 inputs are a sequence of 4 readings of wind speed, ambient temperature and air humidity, taken every 3 hours, in addition to the information of the day, hour and month), having as target is the next wind speed data.

For each technique is applied a two phases study. In the first one, with 80 hidden layer neurons, 1 to 30 training days were used. For each of the techniques, the trainings used 5 rounds and a MAPE average value was found. This first phase selects the network with the best performance. Table 1 shows the combinations of tests and the number of trainings of this phase.

Tab. 1: Combinations of tests (first phase)

1st phase window											
techniques	**input data**		**size of training data**		**target window**		**rounds**		**Number of trainings**		
ELM LRN FFTD DTDNN	Group 1: Wind speed Group 2: wind speed, ambient temperature, air humidity, day, hour and month		1 to 30 days		1 (wind speed for 3 hours ahead)		5				
4	x	2	x	30	x	1	x	5	=	1200	

According to Abelém (1994), while offering advantages, ANN also have limitations. One of the limitations is the lack of procedures to define the precise number of hidden layers or the number of neurons in each of these layers, in other words, the most appropriate configuration for the application. In the second phase, which used the best performance values of the first phase, the number of the hidden layer neurons was varied from 8 to 120, with a step of 8. For each hidden layer neuron, there were five rounds of trainings and an average MAPE was calculated (total of trainings: 1st phase + 2nd phase = 1200 + 600 = 1800).

5. Simulation results

Applying the proposed methodology, the results for group 1, having as input wind speed values of the year 2006 (Table 2), were found. The results of the first phase, which looks for the best performance by varying the number of training days, are found by the average of 5 MAPE values. In the second phase, the number of hidden layer neurons is varied for the best performance found in the first phase. The results of the second phase are found by the average of 5 MAPE values.

Tab. 2: Group 1 results

Group 1	**Input: wind speed for the year 2006**			
technique	**1st phase**		**2nd phase**	
	Training days (1 to 30)		**Number of hidden layer neurons (8-120)**	
	Best Performance (days)	**MAPE (average of 5 rounds)**	**Best Performance**	**MAPE (average of 5 rounds)**
ELM	19	16.23	56	14.05
LRN	24	14.49	104	14.49
FFTD	13	18.60	64	15.48
DTDNN	19	13.79	40	13.96

Analyzing the results of the first phase of group 1, it was observed that networks ELM and DTDNN showed the best performance with 19 days of training. In the second phase, different numbers of hidden layer neurons in each network were observed but with almost the same performance, with MAPE values between 13.96 and 15.48%.

Table 3 shows the results for group 2, having as input the wind speed, ambient temperature, air humidity, day, month and time.

Tab. 3: Group 2 results

Group 2	Inputs: wind speed, ambient temperature, air humidity, day, month and time			
Technique	1st phase		2nd phase	
	Training days (1 to 30)		Number of hidden layer neurons (8-120)	
	Best Performance (days)	MAPE (average of 5 rounds)	Best Performance	MAPE (average of 5 rounds)
ELM	11	14.54	72	13.89
LRN	24	15.76	24	15.78
FFTD	5	17.75	40	18.95
DTDNN	19	14.23	72	13.52

Analyzing the results of the first phase of group 2, it was observed that networks ELM and DTDNN showed the best performance with 11 and 19 days of training, respectively. In the second phase, different numbers of hidden layer neurons in each network were observed but with almost the same performance, with MAPE values between 13.52 and 18.95%.

To verify the validity of the performance values found in table 3 for another year, in this case 2007, for each of the mentioned techniques were applied these values (table 4). As an additional information, table 4 gives the average training time for each technique considering the use of a quad core processor.

Tab. 4: Group 1 results applied to 2007

technique	Best Performance (days)	Best Performance (Number of hidden layer neurons)	MAPE (average of 5 rounds)	average training time
ELM	19	56	25.75	1 min 52 s
LRN	24	104	38.76	55 min 26 s
FFTD	13	64	24.41	5 s
DTDNN	19	40	28.10	6 min 23 s

Similar to the described process, table 5 shows Group 2 results applied to 2007.

Tab. 5: Group 2 results applied to 2007

technique	Best Performance (days)	Best Performance (Number of hidden layer neurons)	MAPE (average of 5 rounds)	average training time
ELM	11	72	37.89	1 min 8 s
LRN	24	24	22.51	7 min 59 s
FFTD	5	40	35.67	4 s
DTDNN	19	72	36	15 min 3 s

6. Conclusions

Many factors influence the ANN performance, as the quantity of input data, training parameters, scale of forecasting and performance evaluation form. In the present paper, as input data were used the wind speed, ambient temperature, air humidity, day, month and time; as training parameters, the number of training days and hidden layer neurons; as scale of forecasting, a 3 hours ahead period; as performance evaluation, MAPE value.

To investigate how the number of training days and hidden layer neurons influence the final result, each network has a own way to achieve the goal of predicting the wind speed with the best performance; this is found by varying the simulation parameters, in this case the number of training days and hidden layer neurons. For the present paper, initial trainings were performed with 3 years of input data. The first results showed MAPE values of around 32 to 40%. These values were not considered satisfactory; so, a second training was started, with a 1 to 30 days training period and with 8 to 120 hidden layer neurons. With this new training period, when seeking the best performance for each type of ANN, it was observed that the networks reached a similar performance, according to tables 3 and 4. As the main conclusion, it can be seen that using only wind speed as input data (Group 1) or using a set of 6 different input data (wind speed, ambient temperature, air humidity, day, month and time) brings no significant difference.

To verify the validity of the performance values found for the year 2006 for the next year, for each of the mentioned techniques were applied these values. It was observed that the best values of 2006 did not keep the same performance when used for 2007. As a possible reason for that process, it is worth to mention that 2006 was a year of ELNIÑO and 2007 was a year of ELNINÕ and LaNina.

Other important information to be considered, it is the average training time. FFTD was always the fastest, followed by ELM; these average times were observed for trainings using a computer with a quadcore processor.

A more robust model that could update dynamically the training would be a way to reduce the ANN results variability and to make the network applicable to different periods of the year.

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