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Short-term wind speed forecasting by combination of neural networks

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Objectives

The aim of this work is to improve the prediction of wind speed in the next hours by the combined use of several artificial neural networks. The employment of Multilayer Perceptron networks (MLP) for a month period with ten-minute values of wind speed and direction and the prior choice of these inputs through classifiers networks such as Self-Organizing Maps (SOM) and Learning Vector Quantization (LVQ) is evaluated. The adjustment obtained in the prediction is compared with different methodologies.

Methods

For the choice of input period is used first SOM neural network. They contain two layers, an input layer and output layer, so that the neurons are connected through adjustable weights or network parameters. The input layer consists of 2 neurons one for each input variable, 10-min values of wind speed and direction on the day before the target. They are chosen for this arrangement only the values of wind speed above 4 m/s. The neighboring function is Gaussian, learning rate is lineal $\alpha(t)=1/t$ and the maximum number of interactions that allowed was 500. The class with the largest number of values and always with a percentage above 40% is used as a criterion for the classification carried out by the LVQ network.

The LVQ networks are composed of three layers, an input layer, a competitive intermediate layer learns to classify input vectors into subclasses and the output layer transforms the competitive layer classes in target classifications. During training a pairs of sample points (x) and their class labels are shown to the learn. The closest feature vector v_w winning feature vector is updated according to one of the following equations, depending on if feature vector v_W classifies sample point x correctly or not. If x and v_W belong to the same class: $v_w(t+1) = v_w(t) + \alpha(t)[x - v_w(t)]$ and If x and v_W belong to different class: $v_w(t+1) = v_w(t) - \alpha(t)[x - v_w(t)]$. The term $\alpha(t)$ controls how large the movement of the feature vector should be in the update. The value of $\alpha(t)$ is updated after each training step as follows: $\alpha(t+1) = \frac{\alpha(t)}{1+p.\alpha(t)}$, where p=1 if sample point is classified correctly and p=-1 in another way. $\alpha(t)$ decrease when a sample is classified correctly and increase when an incorrect classification is made by the winning feature vector. Training parameters were: 0.1 is chosen as $\alpha(0)$, 500 epochs, 2-20 of subclasses range, 120 s of maximum time. Training vectors are presented to the network as input and the Euclidean distance from the input vector to each of the feature vector is computed. Output neurons compete to be activated and only one gets it. The winning neuron is the one whose weight vector is closest to the input vector.

The architecture of the MLP network was for all the simulations: 2 neurons in the input layer (10-min values of wind speed and direction), 5 or 10 neurons in the hidden layer and 1 neuron in the output layer (ten-min values of wind speed) (2_5_1 and 2_10_1). The utilization of MLP networks is divided into two phases, a training phase, during which a set of training patterns is used to determine the weights that define the neural model. For network training ten-minute values of wind speed and direction belonging to a period of 30 consecutive days is chosen.

The data selected correspond to stations located in Northwest Spain (Galicia): Ons (42,38º; -8,93º) at an altitude of 121 m and Punta Candelaria (43,71º; -8,05º) at an altitude of 254 m (Meteogalicia), both on the edge of the coast. Neural Toolbox™ software of MATLAB was used for the creation and resolution of the ANN models. The performance of the models in forecasting accuracy was assessed using the following evaluation criteria: Root Mean Square Error (RMSE), Index of Agreement (IOA), Mean Average Error (MAE). The results obtained are compared with those provided by the persistent pattern and ARIMA (autoregressive integrated moving average) time series models more parsimonious.

Results

Table 1 shows the average values of the errors calculated at 50 simulations. It is notable the significant drop in RMSE (above 30 %) using the proposed method of electing the training period. In the prediction for six hours, the error is less between 6 and 12% respect to 24 hours. In figure 1 the decrease in the RMSE obtained for the next 24 hours after applying the chosen neural networks is observed. Whose horizontal axis represents the class size (%) that constitute the largest group obtained with LVQ network and subsequently used for training the MLP network. IOA and MAE indices obtained for the method proposed against other analyzed options are seen in figures 2 and 3. Only the ARIMA model (2 0 0) has better values.

INPUT (ten-minute speed and direction values)	MODEL	RMSE	
		24 h	6 h
30 previous days to the target	PERSISTENCE	3.36	2.51
	ARIMA (2 0 0)	2.67	1.74
	ARIMA (2 1 0)	3.19	2.23
	2_5_1	4.22	3.12
	2_10_1	4.40	3.02
30 days chosen by means LVQ and SOM (>40 %)	2_5_1	2.83	2.49
	2_10_1	2.75	2.47

Table 1

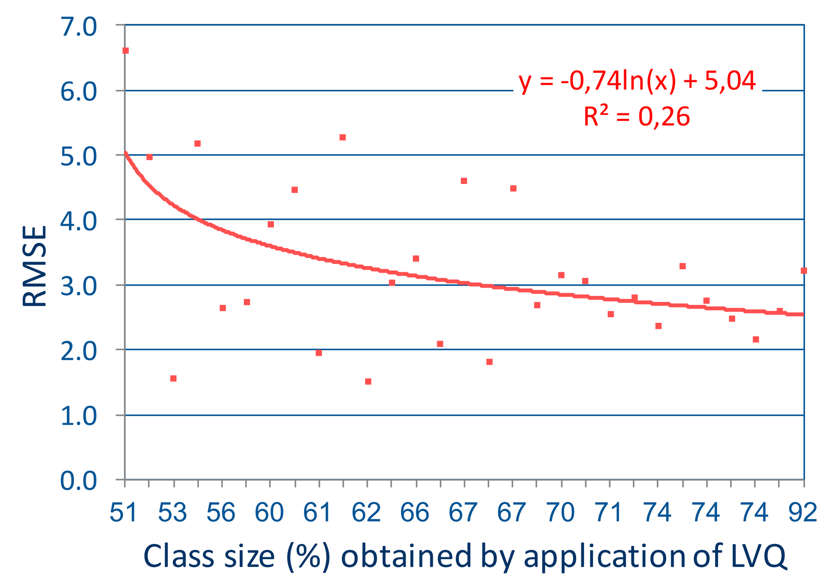

Figure 1

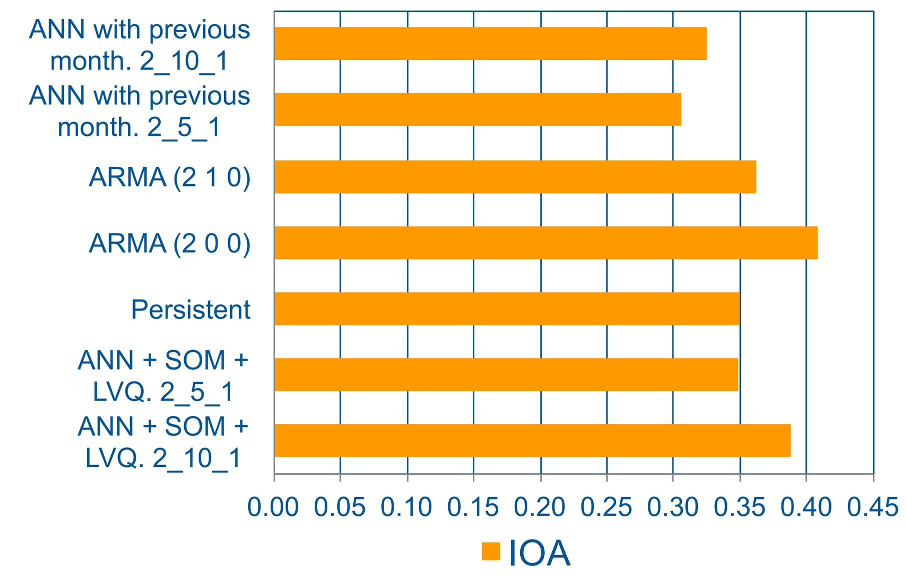

Figure 2

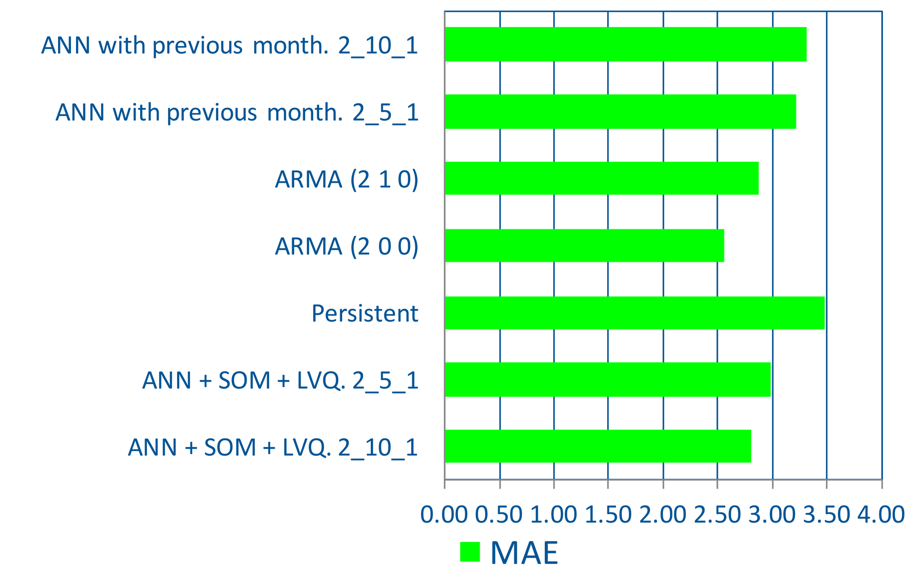

Figure 3

Conclusions

In this work proposes a model to predict the wind speed in the coming hours. The results indicate that using networks LVQ and SOM for input selection improves prediction of the MLP neural networks. The higher the size class obtained by the application of the LVQ network the value of RMSE is reduced. The neural network 2_10_1 in combination with SOM and LVQ provides better results in predicting the speed of the next 24 hours.

References

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