Estimation of wind speed prediction intervals by multi-objective genetic algorithms and neural networks

Ronay Ak, Yanfu Li, Valeria Vitelli, Enrico Zio

Abstract Wind speed forecasting is a fundamental task in wind power production management. In the present work, a multi-objective genetic algorithm (MOGA) is employed to train an artificial neural network (ANN) for short-term forecasting of wind speed prediction intervals.

Introduction

In recent years, power production via renewable energy sources has become quite popular. This is due to both the widespread availability of renewable sources of energy (sun, wind,...) and to the sustainability of the associated production process, which does not cause environmental pollution. Among renewable energy sources, wind plays a key role in meeting the increasing need for electric power.

Wind power production intimately depends on wind speed, which changes with weather conditions. If the variability in wind speed conditions is not properly assessed, power production efficiency and power network operating costs may increase. Therefore, an accurate assessment of the uncertainty associated to wind speed forecasting is critical for the safe, reliable and economic operation of current and future power networks.

In the present work, we use a multi-objective genetic algorithm (namely, Non-dominated Sorting Genetic Algorithm-II, NSGA-II) for finding the optimal weights of an ANN which estimates the prediction intervals (PIs) associated to short-term wind speed forecasting. The ANN weights optimization is sought in Pareto optimality sense, by maximizing the PIs coverage probability (CP) and minimizing the

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PIs width (PIW). This leads to a set of possible solutions of non-dominated PIs, among which the analyst can select the most appropriate for the particular case at hand. An application on real data is illustrated. Hourly wind speed, temperature, relative humidity, pressure and visibility data have been collected for the region of Regina, Saskatchewan, over a period of one month from 21 February 2012 to 21 March 2012. A correlation analysis has been performed to quantify the strength of the relation between the measured parameters. The results of the correlation analysis show that the meteorological parameters measured have weak influence on the wind speed. For this reason, only hourly historical wind speed data have been considered as inputs for the one-hour-ahead prediction of wind speed by ANN. The PIs thereby obtained are satisfactory for wind speed forecast.

1 Methodology

In mathematical terms, the wind speed forecasting problem can be casted as one of nonlinear regression of the kind [6]

$$y = f(x;w) + \varepsilon(x), \quad \varepsilon(x) \sim N(0, \sigma_\varepsilon^2(x)), \tag{1}$$

where x is the vector of regression predictors, y is the target (or response) variable, and w is the vector of model parameters. The term $\varepsilon(x)$ is the random error, which is assumed to be normally distributed with zero mean. The model function f is nonlinear, and its estimation is the purpose of the ANNs training process: in this process of parameter tuning the ANN learns, from the training set of observed input-output data, an approximation of the model function f relating the input to the output.

We here introduce a method for estimating the PI associated to the point estimate $\hat{y}$ obtained as ANN output in correspondence of the input x. The main need for estimating the PI of the ANN output comes from the need of accounting for both the uncertainty in the model structure and the noise in the input data. Two measures are used to evaluate the quality of the estimated PIs: the CP and the PIW. Many methods for estimating PIs in ANN models have been proposed in the literature, i.e. the Delta method, the Bayesian approach, the mean-variance estimation (MVE) and Bootstrap techniques (see [2] for a comprehensive review). However, all these methods consider only the CP but not the PIW. On the contrary, in the method here proposed we account for both within a multi-objective optimization problem of the form

$$\text{min or max } f_m(x), \;\; m = 1,\dots,M; \tag{2}$$

$$\text{subject to } g_j(x) \geq 0, \;\; j = 1,\dots,J; \tag{3}$$

$$h_k(x) = 0, \;\; k = 1,\dots,K; \tag{4}$$

$$x_i^{lb} \leq x_i \leq x_i^{ub}, \;\; i = 1,\dots,n, \tag{5}$$

where the $M = 2$ objective functions f_m measure the CP and PIW, and they are defined as follows

$$f_1 = PICP = \frac{1}{N}\sum_{i=1}^{N} c_i, \tag{6}$$

$$f_2 = NMPIW = \frac{1}{N}\sum_{i=1}^{N} \frac{U(x_i) - L(x_i)}{y_{max} - y_{min}}, \tag{7}$$

where N is the number of samples in the training or test set, $c_i = 1$ if the observed target y_i belongs to the i-th PI= $[L(x_i);U(x_i)]$, 0 otherwise, and y_{max} and y_{min} are the maximum and minimum values of the target in the training set. A solution $x = \{x_1,\dots,x_n\}$ is an n-dimensional decision variable vector in the solution space $\mathbb{R}^n$, which is restricted by the constraints (3-4) and the bounds on the decision variables (5). The goal of the optimization is to identify a set of optimal decision variable vectors x_p^*, $p = 1,\dots,P$, called *Pareto-optimal set*, composed by the solutions that are non-dominated within the entire solution space [4]. The corresponding objective functions values form the so called *Pareto-optimal front* in the objective functions space. The multi-objective optimization problem related to the PI estimation by ANN is here tackled by using the NSGA-II, which is one of the most efficient multi-objective evolutionary algorithms (see [1] for details on this algorithm).

2 Application to wind speed forecasting

We have considered the hourly wind speed, temperature, relative humidity, pressure and visibility, for the region of Regina, Saskatchewan, over a period of one month from 21 February 2012 to 21 March 2012 (data are freely available online, see [3]). These data have been first analyzed with various statistical techniques (see [5]), in order to select a proper set of variables useful for wind speed forecasting. Correlation and principal component analyses (PCA) have been performed to quantify the strength of the relation between the meteorological parameters of temperature, relative humidity, pressure and visibility with the output variable of interest, i.e. the wind speed. The results of the correlation analysis show that wind speed has in fact weak dependence on the meteorological parameters considered (correlation of 22.5%, -26.9%, -18.3% and 1.1% for temperature, relative humidity, pressure and visibility, respectively), while the PCA results show not so neat and interpretable loadings. On the other hand, the analysis of both the autocorrelation and partial autocorrelation functions of the time series of wind speed data clearly show that the three values of wind speed that precede the current one are highly correlated to the current, and hence should be used in the prediction. For this reason, historical wind speed values for three hours before were selected as input variables for the ANN model aimed at providing in output the one-hour-ahead prediction of wind speed. The weights of the ANN model have been determined by application of the NSGA-II, aimed at the optimization of the two objective functions introduced in equations

(6) and (7) above (maximization and minimization, respectively). The two-objective optimization was performed with reference to a training set obtained selecting the first 80% of the available data. Figure 1 (left) shows the Pareto-optimal front: to each point on this front, of coordinates (1-PICP, NMPIW), corresponds a vector of numerical values of the weights of the associated ANN model. On this front, we identify solutions (i.e., trained ANNs) with a normalized interval width inferior to 0.4 (on the y axis in the plot) and a coverage probability higher than 0.95 (i.e., values lower than 0.05 on the x axis in the plot where 1-PICP is reported): we take these two thresholds as minimal requirements for solution acceptability in the context of wind speed forecasting. As an exemplary solution, we take the one pointed by the arrow on the Pareto front, and we report in Figure 1 (right) the wind speed PI estimates (dashed lines) obtained by the corresponding trained ANN on a test set constructed taking the last 20% of the available data: the PIs obtained are quite satisfactory, relative to the target wind speed variable (solid line).

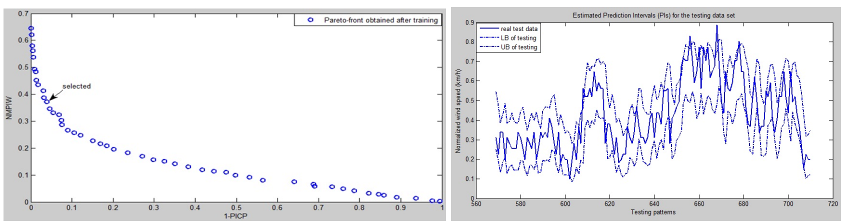

Fig. 1 Left: Pareto-optimal front obtained by NSGA-II. Right: estimated PIs corresponding to the solution pointed by the arrow on the Pareto-optimal front in the left.

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