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EVOLUTIONARY DESIGN OF A GENETIC BASED SELF ORGANIZING NEURAL NETWORK FOR WIND SPEED PREDICTION

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Abstract. *Wind speed prediction is considered as the most crucial task in the implementation of an alternative but at the same time reliable and autonomous electric power source. Accurate wind speed forecasting methods are a significant tool in overcoming a variety of economic and technical problems connected to wind power production. This paper addresses the problem of wind speed forecasting by applying a technique based on the Genetics-Based Self-Organising Network (GBSON) method. Real data were used and real cases were tested based on the measurements of the wind speed provided by Vestas Hellas. The wind speed time series prediction is reformulated to a system identification problem, where the input is the past values of the time series and the output the future values of a time series. This method has been applied in the past to various time series prediction problems giving satisfactory results.*

1 INTRODUCTION

One of the most important factors closely related to both economic and social development nowadays is energy. However most of the electrical energy produced is based on the fossil fuels, which on one hand are highly efficient but on the other are responsible for the emission of greenhouse gases and their reserves, may not last for much longer.

As a result alternative ways have been already adopted for electric power production based on renewable sources such as the wind. It is common knowledge that wind power generation is directly depended on wind speed, which is significantly affected by various factors such as the type of the terrain, the height, any obstacles present and many more. This means that if the reliability of the wind power generation is not at an acceptable level, wind power cannot be used in order to constantly supply electrical energy to the power system. [1, 2].

Artificial Intelligence is amongst a set of methods that offer robust solutions and can be efficiently implemented to various real life problems in diverging fields such as medicine, chemical processes, computer network topology, economics, fuel management and many more [3, 4, 5, 6, 7, 8].

In this paper artificial intelligence and more specifically the Genetics-Based Self-Organizing Network (GBSON) method [9] is applied to the wind speed estimation and prediction problem, using real data provided by Vestas Hellas®, giving satisfactory results. The same technique has been already applied and tested to another real problem concerning the prediction of the thunderstorm days in Greece, producing very good results [10, 11].

2 METHOD PRESENTATION

The technique proposed is a hybrid method that combines the Group Method of Data Handling (GMDH) and Genetic Algorithms [12]. Its main advantage is its ability to overcome the drawbacks of the original GMDH algorithms, since they use local search techniques to obtain an optimal solution [13, 14].

The proposed method uses polynomial neural networks to represent the model of the system to be identified.

Each layer of the polynomial neural network is regarded as a separate optimization problem. The input to the first layer of the network is the independent variables of the data sample. The output of each layer is the peak nodes obtained by the use of a multi-modal Genetic Algorithm [15]. The peak nodes selected to be the output of a layer are also the inputs for the next layer.

The population members of the GA are network nodes represented by an eight-field bit string. The two first fields are used to represent the nodes from the previous layer connected to the present node. The other six fields are used to represent the coefficients of a quadratic function that determines the output of the node y:

$$y = bz_1 + cz_2 + dz_1 z_2 + ez_1^2 z_2^2 \tag{1}$$

where z_1, z_2 are the outputs of the connected nodes in the previous layer.

The fitness measure of a node is given by calculating its description length. The description length gives a trade off between the accuracy of the prediction and the complexity of the network. The equation used by Kargupta and Smith for calculating the description length is:

$$I = 0.5n \log D_n^2 + 0.5m \log n \tag{2}$$

where D_n^2 is the mean-square error, m is the number of coefficients in the model selected and n is the number of observations used to determine the mean-square error.

The multi-modal GA used in GBSON incorporates the fitness-sharing scheme, where the shared fitness is given by:

$$f_i' = \frac{f_i}{m_i} \tag{3}$$

f_i is the original fitness of the node and m_i is a niche count defined by:

$$m_i = \sum_{j=1}^{N} sh(d_{ij}) \tag{4}$$

where

$$sh(d_{ij}) = \begin{cases} 1 - \left(\dfrac{d_{ij}}{\sigma_s} \right)^a & \text{if } d_{ij} < \sigma_s \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

N is the population size and d_{ij} is the Hamming distance between the members of the population i and j. The niche radius σ_s is determined by the equation:

$$\frac{1}{2^l} \sum_{i=0}^{\sigma_s} \binom{l}{i} = \frac{l}{q} \tag{6}$$

where l is the string length and q is the number of nodes in the previous network layer.

New populations are obtained after applying the genetic operators of tournament selection, single-point crossover and point mutation. A mating restriction is also applied to the members to be crossed. If a member i is to be crossed, its mate j is selected such that $d_{ij} < \sigma_s$. If no such mate can be found then j is selected randomly.

The GBSON procedure continues until the GA converges to a layer with a single node.

3 THE WIND SPEED SERIES

A number of simulations was conducted based on the hour average of daily wind speed recorded by the Vestas Hellas from November 2010 up to February 2011. The obtained time series did not follow any periodic pattern and it was also presenting irregular amplitudes, making it hard to predict (Figure 1).

The task of this work is to generate a single-step prediction based on past observations. The data were normalized to take values from zero to one, before using them as input data to the polynomial neural networks. The input pattern was assigned as (x(t-1), x(t-2), x(t-3)) and the desired output was:

$$x(t) = f((x(t-1), x(t-2), x(t-3)) \tag{7}$$

From the 2725 available data points, 530 points (1770 to 2300) were used for the validation of potential models. The simulations were run with a population size of 80 for 150 generations, with tournament size 6, probability of crossover 0.95 and probability of mutation 0.02.

GBSON resulted to a network with three layers to model the wind speed time series. The most significant term in the partial descriptions,

$$y = a + bx_i + cx_j + dx_i x_j + ex_i^2 + fx_j^2 \tag{8}$$

of the model was the term x_j and the less significant term was the constant term. The past values of the wind speed series, (x(t-1), x(t-2), x(t-3)), contributed equally to obtain the final model.

The results of the prediction can be seen in Figure 2. The actual error of the prediction is shown in Figure 3. The percent square error (PSE) over the whole data set is 3.0% and the root mean square error (RMSE) is 0.4925. The PSE over the validation data set is 3.15%. The difference of the PSE over the whole data set and the validation data set is small, and thus the model obtained can be considered to perform with approximately the same accuracy in data points that have not been used in any part of the modelling process.

4 CONCLUSIONS

The paper has presented the use of artificial intelligence and more specifically artificial neural networks, genetic algorithms and evolutionary algorithms in the solution of the time series prediction problem. The time series prediction problem has been formulated as a system identification problem, where the input to the system was the past values of a time series, and its desired output is the future values of a time series. A method has been developed based on the well known from the literature Genetics-Based Self-Organising Network (GBSON) method and has been applied to real data producing acceptable results. However further work needs to be done on the fine tuning of the neural network parameters in order to reduce the PSE. Additionally the ability of the proposed method for on-line prediction should be tested as well.

5 FIGURES

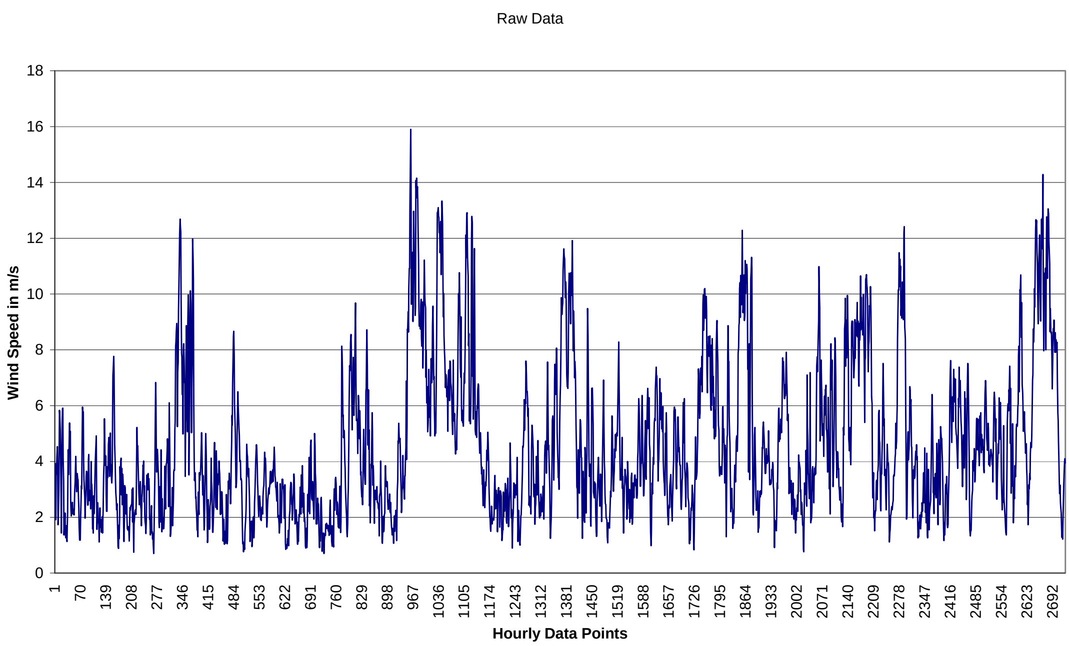

Figure 1. Hourly averaged wind speed time series, 1/11/2010 – 22/2/2011.

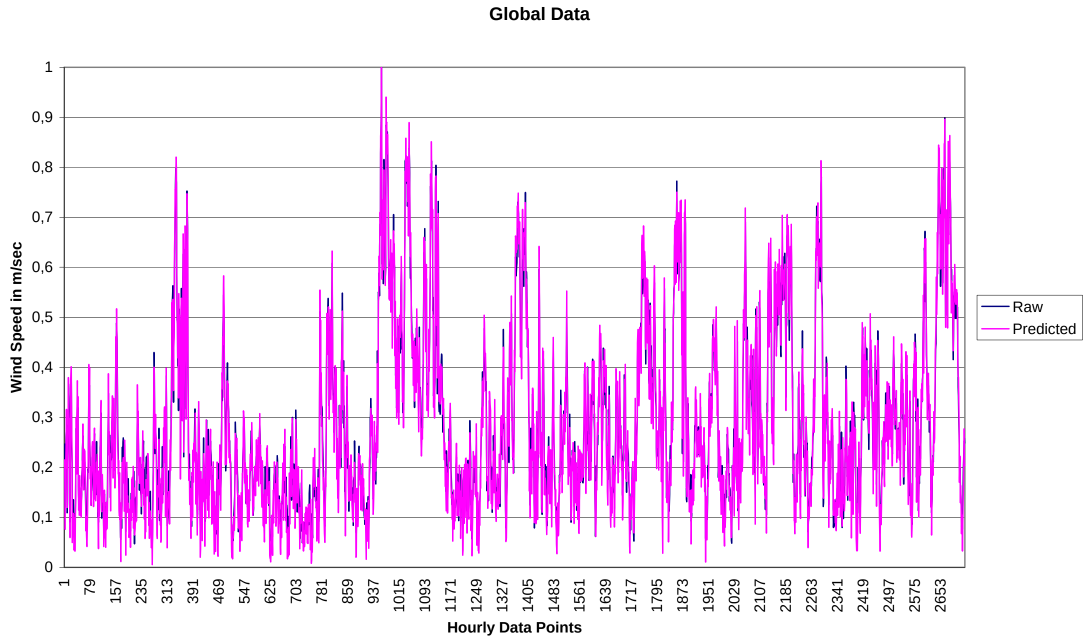

Figure 2.The actual (normalized) wind speed series and the predicted with the proposed method.

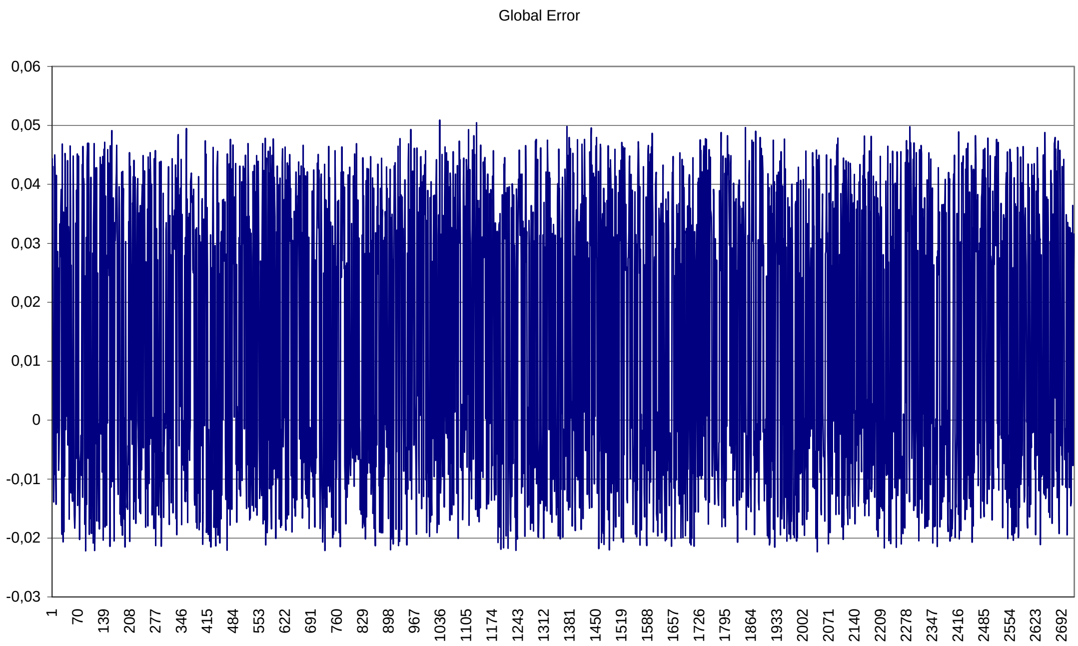

Figure 3.The actual error for each point of the wind speed time series predicted by the proposed method.

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