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Bipolar Extreme Learning Machine for solar and wind synergy regression

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Abstract. The authors propose a Bipolar Extreme Learning Machine approach for solar and wind synergy regression. The solar and wind synergy is relevant because it is critical in many renewable energies. It is used in processes such as biofuels production, food industry, detergents and dyes in powder production, reprography applications, textile industries, pharmaceutical industry and others. The results are tested with the state-of-the-art techniques (linear regression, k-Nearest Neighbours regression, Random Forest and Support Vector Regression) and our proposal outperforms them. In addition, the experiments have been benchmarked with two error measures (MAE and MSE).

Keywords: Extreme Learning Machines, regression, solar and wind synergy

1 Introduction

Extreme Learning Machines (ELMs) are Single Hidden Layer Feedforward Neural Networks where the weights of the neurons in the hidden layer are randomly generated [6]. In this paper, we propose a Bipolar ELM approach with hidden layer generates with a gaussian zero-centered distribution for solar and wind synergy regression.

The moisture loss because of the solar and wind synergy is a difficult issue with related uncertainties and risks. It involves two simultaneous processes: transfer of mass and transfer of heat, with the possible emergence of chemical, physical and even biological transformation effects.

The remainder of this paper is organized as follows. First, in Section 2 we show a brief background on Extreme Learning Machines. Section 3 details the experimental proposal and shows the results of the experiments and the last section concludes the paper.

2 Extreme Learning Machines

Extreme Learning Machines (ELMs) is a machine learning technique with and outstanding generalization performance and extremely fast learning speed [1].

ELMs [3] are Single Hidden Layer Neural Networks with a novel feature: the weights of the hidden neurons (from input weights and biases) are randomly assigned

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(Figure 1). The weights of the edges between the hidden layer and the output layer could be determined according to the Moore-Penrose generalized inverse and the smallest norm least-squares solution of general linear system. It is an accurate learning method without any learning iteration [7].

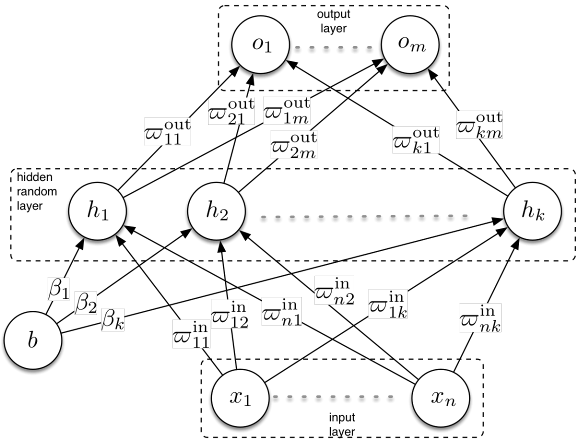

Fig. 1. Extreme Learning Machine

Let Ψ a training dataset $\Psi = \{\mathbf{x}_i, \mathbf{o}_i\}_{i=1}^{c}$ where c is the number of instances, $\mathbf{x}_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T$ with n features (inputs) and $\mathbf{o}_i = [o_{i1}, o_{i2}, \ldots, o_{im}]^T$ the labels (outputs). The input and hidden layer are connected by a $n \times k$ weight matrix where the ith row vector is denoted as $\varpi_i^{\text{in}} = \left[\varpi_{i1}^{\text{in}}, \varpi_{i2}^{\text{in}}, \ldots, \varpi_{ik}^{\text{in}}\right]^T$ where $\varpi_i^{\text{in}} \in \Re^k$.

Each neuron of the hidden layers has a bias modeled by a row vector $k \times 1$ as $\beta = [\beta_1, \ldots, \beta_k]$. The hidden and the output layers are connected by an adjacency matrix $k \times m$ where the jth row vector is denoted as $\varpi_j^{\text{out}} = [\varpi_{j1}^{\text{out}}, \varpi_{j2}^{\text{out}}, \ldots, \varpi_{jm}^{\text{out}}]^T$ where $\varpi_j^{\text{out}} \in \Re^m$. The output of the ELM is a row vector denoted by $\mathbf{O} \in \Re^m$.

The weight of the neurons in the hidden layer and the bias are randomly generated. In our proposal, the authors apply a zero-centered gaussian random generator as follows

$$G(x) = \frac{1}{\sigma \cdot \sqrt{2\pi}} \cdot e^{-\frac{(x-\mu)^2}{2 \cdot \sigma^2}} \tag{1}$$

where the standard deviation is $\sigma = 1.0$ and the center of the distribution is $\mu = 0$. It generates a bipolar gaussian distribution around zero.

The output of the ith neuron is computed as follows

$$\mathbf{o}_i = \sum_{j=1}^{m} \varpi_j^{\text{out}} \cdot f\left(h_i\right) \tag{2}$$

where $f(\cdot)$ is the activation function and $\varpi_j^{\text{in}} \cdot x_i$ is the inner product between the values of the input layer and the weights of the edges from the input to hidden layer. Eq. 2 can be written in a more compact way as follows

$$\mathbf{H} \cdot \varpi^{\text{out}} = \mathbf{O} \tag{3}$$

where $\mathbf{H} \in \Re^{n \times k}$ is the following adjacency matrix

$$\mathbf{H} = \begin{bmatrix} f\left(\varpi_1^{\text{in}} \cdot x_1 + \beta_1\right) & \dots & f\left(\varpi_k^{\text{in}} \cdot x_1 + \beta_k\right) \\ \vdots & \ddots & \vdots \\ f\left(\varpi_1^{\text{in}} \cdot x_n + \beta_1\right) & \dots & f\left(\varpi_k^{\text{in}} \cdot x_n + \beta_k\right) \end{bmatrix} \tag{4}$$

It is possible to use several activation functions. The most common ones are unipolar sigmoid and hyperbolic tangent.

$$f(\varpi_j^{\text{in}}, \beta_j, x_i) = \frac{1}{1 + e^{\varpi_j^{\text{in}} \cdot x_i + \beta_j}} \tag{5a}$$

$$f(\varpi_j^{\text{in}}, \beta_j, x_i) = \frac{\sinh\left(\varpi_j^{\text{in}} \cdot x_i + \beta_j\right)}{\cosh\left(\varpi_j^{\text{in}} \cdot x_i + \beta_j\right)} \tag{5b}$$

If hyperbolic tangent is the activation function then Eq. 4 can be computed, according to Eq. 5b, as follows

$$\mathbf{H} = \begin{bmatrix} \frac{\sinh\left(\varpi_1^{\text{in}} \cdot x_1 + \beta_1\right)}{\cosh\left(\varpi_1^{\text{in}} \cdot x_1 + \beta_1\right)} & \dots & \frac{\sinh\left(\varpi_k^{\text{in}} \cdot x_1 + \beta_k\right)}{\cosh\left(\varpi_k^{\text{in}} \cdot x_1 + \beta_k\right)} \\ \vdots & \ddots & \vdots \\ \frac{\sinh\left(\varpi_1^{\text{in}} \cdot x_n + \beta_1\right)}{\cosh\left(\varpi_1^{\text{in}} \cdot x_n + \beta_1\right)} & \dots & \frac{\sinh\left(\varpi_k^{\text{in}} \cdot x_n + \beta_k\right)}{\cosh\left(\varpi_k^{\text{in}} \cdot x_n + \beta_k\right)} \end{bmatrix} \tag{6}$$

In ELMs, the weights of the connections between hidden layer and the output weights can be computed analytically as

$$\varpi^{\text{out}} = \mathbf{H}^{\dagger} \cdot \mathbf{O} \tag{7}$$

where $\mathbf{H}^{\dagger} = (\mathbf{H}^{\mathbf{T}}\mathbf{H})^{-1}\mathbf{H}^{\mathbf{T}}$ is the Moore-Penrose generalized inverse of the matrix $\mathbf{H}$ [4].

3 Experimental approach

The complementary mixed attributes of wind and sun have been analyzed in the literature [2]. The impact of sun and wind can modify the features of an object to dry and turn the transmission of heat and mass. So, experimental testing keeping the relevant external variables (humidity, rate, temperature, airflow direction, physical shape and so on) are critical for the regression of the moisture loss and dryer machines design.

The samples of covers and seeds were gathered from the wastewater treatment plant of a tomato factory located in the Southwest area of Spain. They got an initial moisture content 63% by weight (wet basis). This value was estimated according to the Standard UNE 32001 [5].

Experiments were conducted at three drying air temperatures (30°C, 40°C and 50°C) and at two air velocities (0.9 m/s and 1.3 m/s) and according to the cited methodology. The results of the experiment are shown in Table 1. ELMs achieved the lower error measurement for MAE and MSE. According to the error measures, our proposal outperforms the state-of-the-art techniques.

Table 1. Error measures

	MAE	MSE
Linear Regression	0.1395	0.0324
k-NN	0.0223	0.0030
Random Forest	0.0142	0.0005
Support Vector Regression	0.0525	0.0042
Bipolar-ELM	**0.0016**	**8.02e-06**

4 Conclusions

In this paper, we proposed a Bipolar Extreme Learning Machine for sun and wind synergy regression. The authors compare several state-of-the-art techniques and the ELM proposal. Moreover, a range of number of neurons in the hidden layer is checked.

The authors applied the proposal to the tomatoes' cover drying process. As far as we know, this is a novel application of Extreme Learning Machines. In addition, the authors apply several error measurements for checking the worth of the proposal.

According to this, the results of the experiments proof that our ELM's proposal outperforms the state-of-the-art algorithms.

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