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Optimized extreme learning machine using genetic algorithm for short-term wind power prediction

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ABSTRACT

Through the much defiance facing energy today, it has become necessary to rely on wind energy as a source of unlimited renewable energies. However, energy planning and regulation require wind capacity forecasting, because oscillations of wind speed drastically affect directly power generation. Therefore, several scenarios must be provided to allow for estimating uncertainties. To deal with this problem, this paper exploits the major advantages of the regularized extreme learning machine algorithm (R-ELM) and thus proposes a model for predicting the wind energy generated for the next hour based on the time series of wind speed. The R-ELM is combined with the genetic algorithm which is designed to optimize the most important hyperparameter which is the number of hidden neurons. Thus, the proposed model aims to forecast the average wind power per hour based on the wind speed of the previous hours. The results obtained showed that the proposed method is much better than those reported in the literature concerning the precision of the prediction and the time convergence.

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1. INTRODUCTION

In recent years, the environmental problems caused by climate change and traditional fossil fuels have become increasingly serious. Using sustainable renewable energy (RE) sources guards against environmental deterioration and shields the atmosphere from the hazards and disruptions of nuclear power [1], [2]. The fact that RE is powered by renewable resources such as the sun, wind, and water results in lower costs. Creating clean, green power also contributes to lowering pollutants and CO_2 emissions.

The fundamentals of electricity production are largely the same for all RE sources. Especially, wind power is the most widely used to generate electricity using wind turbines [3]. Wind energy is environmentally friendly as it can be used easily, so it is an ideal source of renewable energy on a large scale. But during its rapid development, it faced many challenges. Wind energy is affected by many effects such as wind speed, which in turn is changeable, inconstant, and intermittent because of the large fluctuations in wind power production. Due to this extreme variability, wind energy integration is facing significant challenges. The impact of the hazard can be minimized by the wind speed forecasting model [4], [5].

To predict wind energy, many strategies have been improved, which are divided into three categories: statistical and physical methods and artificial intelligence models [6]. Statistical approaches including automatic regression (AR) and auto-regressive integrated moving average (ARIMA) are best implemented than digital weather models in short-term forecasting, so it is considered a modest method [7]. However, due to the linearity of statistical approaches, they cannot correctly predict nonlinear and nonstationary wind energy [8]. Physical prediction approaches like numerical weather prediction (NWP) methods, when the environment is constant, they show high precision in long-range forecasting [9], [10]. Nevertheless, the computational complexity of the accuracy of these models is greatly increased by the complex information requirements of the atmosphere [11]. Artificial intelligence approaches like least squares support vector machines (LSSVM) [12], artificial neural networks (ANN), and back-propagation algorithms (BP) are powerful and broadly applied to wind energy forecasting with suitable precision. The ANN is more favored due to its nonlinear system, which can take the fuzzy functional relationship of historical time series [13]. Also noted is that the strong properties of ANNs make them an effective tool for wind energy prediction. For instance, [14] based on the hourly average wind speed data, performed a comprehensive comparative study of the forecast performance of three different ANNs. Meng *et al*. [15] described that ANN has several advantages over other models no supplementary information is needed other than historical wind speed data. Moreover, Kani and Ardehali [16] proposed a new technique for predicting short-range wind speeds using ANN and Markov chains. Moreover, wavelet neural network (WNN) is an ideal prediction tool with advanced convergence speed and excellent results, so it is one of the most efficient artificial neural networks. That has been broadly used for time series forecasting in any domain such as wind power forecasting [17].

These suggested works are all built on supervised learning. On the contrary, they experience some anxiety. The main drawbacks of these models are the local minima they can reach and the slow convergence time. Also, they are reliant on the input data and perform poorly with large datasets or when the dataset has more noise. Ultimately, these models are incapable of adjusting to significant changes in meteorological data [18].

Taking into account these issues, this article proposes a novel model to evaluate the quantity of wind energy produced founded on the regularized extreme learning machine (R-ELM) algorithm. R-ELM is founded on the main minimization of structural risk and weighted least squares. It fixes the issues with the algorithms mentioned that are used to wind energy forecast. The implementation of the R-ELM algorithm generalization is significantly ameliorated in many instances without increasing the learning time [19]. Due to the concealed nodes' connection weights being spread at random and never being updated. We take as inputs of the proposed wind energy forecasting model the previous wind speed which forms a time series. While the output is the next energy generated by the wind turbines. In the hidden layer, the number of nodes is a large hyperparameter that greatly affects the execution of the final output of the model. In this regard, the genetic algorithm (GA) is applied in this paper to improve the hidden neurons of the proposed R-ELM model. GA is a computation technique intended to optimize a problem by iteratively attempting to make the result better following a fitness function [20]–[26]. It has shown a strong capability in the optimization field compared to optimization techniques such as particle swarm optimization (PSO) [27] and ant colony (AC) [28]. The suggested model is called regularized extreme learning machine algorithm genetic algorithm (R-ELM-GA).

The remainder of this article is organized in the following way. In heading 2 we introduce the ELM algorithm and R-ELM algorithm, and next, we expose the GA, and we provide an elaborate description of the suggested wind energy forecast founded on R-ELM-GA. In section 3 we present the results of the simulation. We conclude the paper in section 4.

2. METHOD

2.1. Extreme learning machine

ELM which is introduced in [29] is a forward neural network with a powerful hidden layer that is detected by feedback. The main components of the ELM construction are the input layer, the output layer, and the hidden layer, connected by links called weights. The initial input weights are chosen at random, and the output weights are established using the inverse Moore-Penrose function [30]. ELM outperforms other machine learning techniques when the computational value is low.

Taking into account a single-hidden layer feedforward neural network (SLFN), we will suppose that it has a training set $\{(x_i, t_i)\}_{i=1}^{N}$ with N separated instances, where $x_i = [\,x_{i1}; x_{i2}; \ldots\ldots; x_{in}]^T$ include n inputs and $t_i = [t_{i1}; t_{i2}; \ldots\ldots; t_{im}]^T$ includes m outputs, and $g(x)$ the function that activates the hidden layer's output, then the generic result t_i maybe placed into the outcome target following the subsequent function:

$$\sum_{j=1}^{L} \beta_j g\left(\omega_j . x_i + b_j\right) \tag{1}$$

Where ϖ_j and b_j are the randomly attributed parameters; β is the weight of the linking between the hidden nodes and the output nodes illustrated in Figure 1.

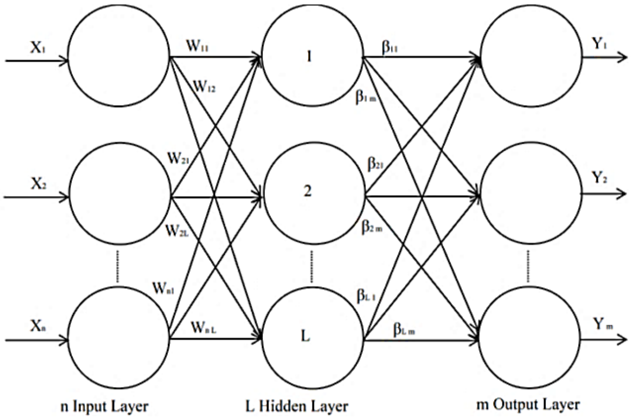

Figure 1. Representation of the ELM construct

There are two key stages to the ELM learning phase. As previously mentioned, the hidden layer's weights and biases are first created at random. The following equation may then be used to calculate an exact approximation of the input samples:

$$H\,\beta = T \tag{2}$$

$$\text{where } H = \begin{bmatrix} g(\omega_1 x_1 + b_1) & \cdots & g(\omega_1 x_1 + b_L \\ \vdots & \ddots & \vdots \\ g(\omega_1 x_N + b_1) & \cdots & g(\omega_1 x_N + b_L \end{bmatrix}_{N\times L} \tag{3}$$

and $T = [t_1; t_2; \ldots; t_N]^T$. In the second stage, making use of the generalized Moore-Penrose inverse of the hidden layer matrix $H^{\dagger}$, the output weights are computed:

$$\beta = H^{\dagger}T \tag{4}$$

where the Moore-Penrose pseudo-inverse of H is denoted by $H^{\dagger}$.

2.2. Regularized extreme learning machine

Recently, ELM has gained great celebrity, and then due to its speed and good generalization execution, it has been successfully applied in various fields. However, it can even be examined as an empirical subject of risk reduction and tends to create an overfitting model [21]. Furthermore, it can train less reliable estimates, especially with the existence of heterogeneous values or events in the data. Finally, ELM can provide less control because it directly computes the least-squares solution of the weakest criterion [31] to fill these gaps, Deng *et al.* [31] suggested a new algorithm named R-ELM founded on the principle of structural risk minimization (SRM) and the weighted least squares method. In general, when you want to configure SLFN, you have to find ω_i, b_i, β ($i = 1 \ldots L$) like this:

$$\begin{gathered} min\ \|\varepsilon\|^2 \\ s.t\ \sum_{j=0}^{L} \beta_j g(\omega_j . x_i + b_j) - t_i = \varepsilon_i \\ i = 1, \ldots, N \end{gathered} \tag{5}$$

Where $\varepsilon_i = \varepsilon_{i1}, \varepsilon_{i2}, \ldots\ldots, \varepsilon_{im}$ is the evaluator among the actual value and objective value of the i-th specimen, and $\varepsilon = \varepsilon_1, \varepsilon_2, \ldots\ldots, \varepsilon_n$. However, a well-generalized model should achieve the best solution despite the empirical risks and structural risks, which in turn constitute the real danger of prediction by learning statistics theory. By presenting a weighting factor γ for the empirical risk, which is depicted by the sum of the squares of the errors i.e., $\|\varepsilon\|^2$, their proportions can be regularized, and the structural risk can be depicted by $\|\beta\|^2$ which is a value to maximize the distance to the edge disconnecting between boundary categories. In addition, to obtain a robust estimate that attenuates the anomalous interferences, the error ε_i is weighted by the variable v_i. Thus, $\|\varepsilon\|^2$ is prolonged to $\|D_\varepsilon\|^2$, where $D = diag(v_1, v_2, \ldots.., v_N)$.

Therefore, we can be depicted the mathematical model of the proposed R-ELM algorithm as (6):

$$\min \frac{1}{2}\|\varepsilon\|^2 + \frac{1}{2}\gamma\|D_\varepsilon\|^2$$
$$s.t\ \sum_{j=0}^{L}\beta_j g(\omega_j.x_i + b_j) - t_i = \varepsilon_i \quad (6)$$
$$i = 1,2,\dots,N$$

To determine the optimal balance between the ratio of structural risk and empirical risk, any individual can adopt this ratio by adjusting these two risks, resulting in a model with good generalization performance. We can be depicted the Lagrangian function of (6) as (7):

$$L = (\beta,\varepsilon,\alpha) = \frac{1}{2}\gamma\|D_\varepsilon\|^2 + \frac{1}{2}\|\beta\|^2 - \sum_{i=1}^{N}\alpha_i$$
$$\left(\sum_{j=0}^{L}\beta_j g(\omega_j.x_i + b_j) - t_i - \varepsilon_i\right) = \frac{1}{2}\gamma\|D_\varepsilon\|^2 + \frac{1}{2}\|\beta\|^2 - \alpha(H\beta - T - \varepsilon) \quad (7)$$

where $\alpha_i \in \mathbb{R}\,(i = 1,\dots,N)$ is the Lagrange multiplier with equality restrictions from (6) and $\alpha = [\alpha_1;\ \alpha_2; \dots ;\ \alpha_N]$. Then, by setting the gradient of this Lagrangian to zero for $(\beta,\ \varepsilon,\ \alpha)$, the optimal conditions are obtained as (8):

$$\begin{cases} \frac{\partial L}{\partial \beta} \rightarrow \beta^T = \alpha T, \\ \frac{\partial L}{\partial \varepsilon} \rightarrow \gamma\varepsilon^T D^2 + \alpha = 0\,, \\ \frac{\partial L}{\partial \alpha} \rightarrow H\beta - T - \varepsilon = 0\,. \end{cases} \quad (8)$$

Replacing the latter formula of (8) in the second formula will result in a clear formula for α (9) and ε_i can be computed with α (10):

$$\alpha = -\gamma(H\beta - T)^T \quad (9)$$

$$\varepsilon_i = \frac{\alpha_i}{\gamma} \quad (10)$$

By resolving (8), we can get the solution of β:

$$\beta = \left(\frac{I}{\gamma} + H^T D^2 H\right)^{\dagger} H^T D^2 T \quad (11)$$

where I is a unitary matrix. When D is the unitary matrix I, we can use the following expression to calculate β:

$$\beta = \left(\frac{I}{\gamma} + H^T H\right)^{\dagger} H^T T \quad (12)$$

The algorithm is named unweighted regularized ELM (UWR-ELM) in this case. Indeed, when $\gamma \rightarrow \infty$ the traditional ELM is a special case of the ELM-UWR. There are many types of calculation methods to obtain the weights v_i, such as (13):

$$v_i = \begin{cases} 1 & \left|\frac{\varepsilon_i}{\hat{s}}\right| \le c_1 \\ \frac{c_1 - \left|\frac{\varepsilon_i}{\hat{s}}\right|}{c_1 - c_2} & c_1 \le \left|\frac{\varepsilon_i}{\hat{s}}\right| \le c_2 \\ 10^{-4} & otherwise \end{cases} \quad (13)$$

where the constant c_1 and c_2 are usually set at 2.5 and 3 consecutively. We can compute ŝ which is a robust estimate of the standard deviation of unweighted error variables ε_i is as (14):

$$\hat{s} = \frac{IQR}{2\times 0{,}6745} \quad (14)$$

where IQR is the interquartile interval that is the variance between the 25th percentile and the 75th percentile.

2.3. Genetic algorithm

The genetic algorithm is a Darwinian developmental simulation of natural selection and the process computational model of the genetic mechanism of biological evolution proposed by [22]. It is an extensive simulation of the natural evolution method of optimal solutions to some complex problems. At the core of the genetic algorithm are initial group identification, parameter encoding, genetic manipulation, fitness function, and control parameters [23]. The genetic process principally contains three factors: the selection process, the crossing process, and the variation process. The control parameters primarily contain group size and the probability of genetic functioning.

2.4. Proposed method

One of the most important and best sources of renewable energy is wind energy, which is considered appropriate, promising, and active, attracting more and more global attention, thanks to its ambitious advantages such as environmental protection and ease of use. Wind turbines generate wind energy by turning the kinetic energy of the wind into usable power. The power delivered by this generator can be calculated as (15) [32]:

$$P_W = \begin{cases} 0 \; si \; V < V_{min} \\ aV^2 + bV + c \; si \; V_{min} \leq V < V_r \\ P_{WN} \; si \; V_r \leq V > V_{max} \end{cases} \tag{15}$$

where:
P_{WN}: the estimated produced energy of the wind turbine
V: wind speed
V_{min}: the wind speed required to trigger the wind turbine
V_{max}: the cut-off wind speed of the wind turbine
V_r: estimated wind speed
a, b, and c: constants and depend on the wind turbine type

The main drawback of wind power is the great variability of wind speed that makes it difficult to control and optimize the operation of power production. It leads to significant challenges in the planning of reliable wind power systems and also affects their rapid development. Due to this extreme variability, the integration of wind power inside the grid faces significant challenges. Consequently, the effects of the fluctuating wind speed can be minimized by building a prediction model to evaluate the wind power produced. To determine the power output generated, meteorological measurements like wind speed are taken as inputs because the efficiency of the generation unit depends on the weather conditions.

In the literature, there are several works on the prediction of wind energy generation. However, they suffer from some difficulties such as local minimum and slow convergence time. R-ELM is a strong algorithm that has proved its capability to solve the shortcomings.

In this regard, in this article, we propose a model for forecasting wind energy that combines the R-ELM algorithm and GA. The proposed model exploits the most advantages of the R-ELM algorithm (extreme time convergence and good generalization ability) while optimizing the hyperparameter of hidden nodes number using the GA. Since the past wind speed restrains hidden information and correlation that affect the next wind power generated, then we built a prediction model with wind speed values as inputs of the network. The final production corresponds to the hourly wind energy produced. According to the work of [19], to correlate past wind speed values with the next wind speed value, only 8 past wind speed values are sufficient, so we opt for 8 entries for the last wind speed. The developed model, designated as R-ELM-GA, can make use of the main features of the R-ELM technique while eliminating the random selection of the hidden node number or the recurrent tests that need more training time and result in slower convergence. Following [33], we can determine the hidden nodes' L number in the hidden layer as (16):

$$L = \sqrt{n+m} + \alpha \tag{16}$$

where α is a constant and $1 \leq \alpha \leq 10$.

The number of inputs in our model is eight and the number of the output is one. The hidden nodes number L might thus range from 4 and 13 according to (16). The set {4, …,13} is seen as a population of unique solutions for the GA, where the mean square error (MSE) is regarded as fitness or an objective function. The many phases of the R-ELM-GA method are presented in a flowchart in Figure 2.

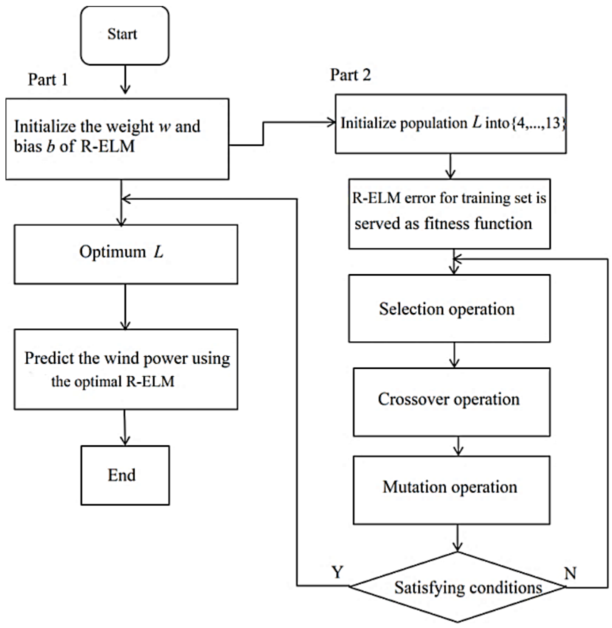

Figure 2. The different steps of the R-ELM-GA algorithm

3. RESULTS AND DISCUSSION

In this section, we will introduce the results and discuss the numerical analyses. To evaluate the effectiveness of the suggested wind prediction R-ELM-GA model, we used a set of wind speeds from Tetouan City in Morocco [30]. The dataset for the modeling has been divided into training and testing sets. As a result, we used 70% of the instances in the training set to train the model and 30% of the examples in the test set to evaluate its performance.

The Python language is used to implement the R-ELM-GA method. There are one output node and eight input nodes in the whole network. The GA approach was used to optimize the number of concealed nodes into the set of {4, ...,13}. As a consequence, the optimization procedure determined L be optimum at 12. To enhance and measure the forecasting performance of the model, we conducted a comparison etude using the most used algorithm in wind energy forecasting, namely the R-ELM [34], the fundamental ELM [30], the BP [14], and the support vector machines (SVM) [35] algorithms.

To study the efficacy of the suggested model and its ability to better perform in the critical season, we have added an examination of contrasts for the summer and winter months, respectively. The forecast results are presented in Figures 3-7 where we compared the results of the BP, SVM, ELM, R-ELM, and R-ELM-GA models respectively, and the examined measures for one month in summer. In Figures 8-12, we have exposed the comparison result of the BP, SVM, ELM, R-ELM, and R-ELM-GA models respectively, and the examined measures for one month in winter. Based on these figures, the R-ELM-GA model has good prediction measures in both the summer and winter seasons, as its curve closely resembles the observed curve.

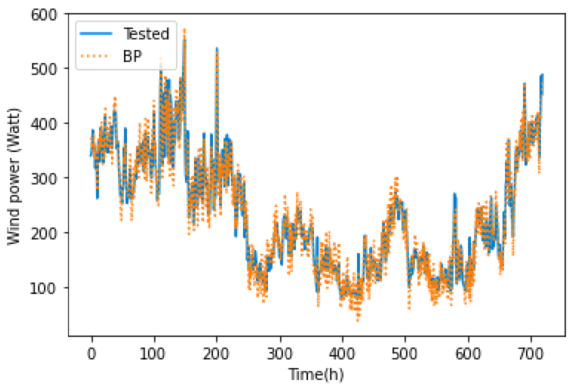

Figure 3. Wind power predicted by BP in summer

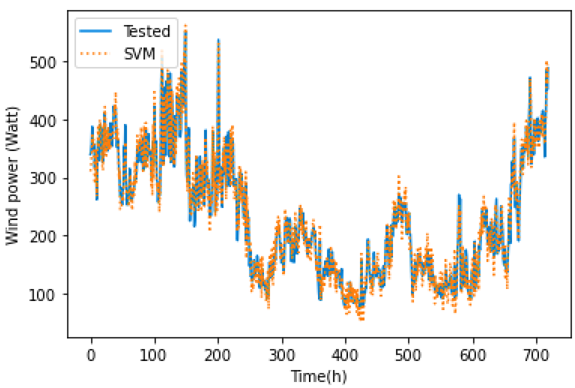

Figure 4. Wind power predicted by SVM in summer

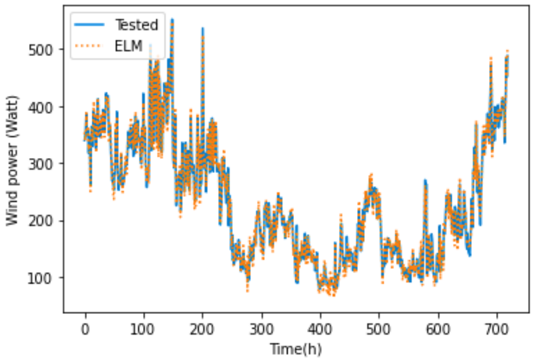

Figure 5. Wind power predicted by ELM in summer

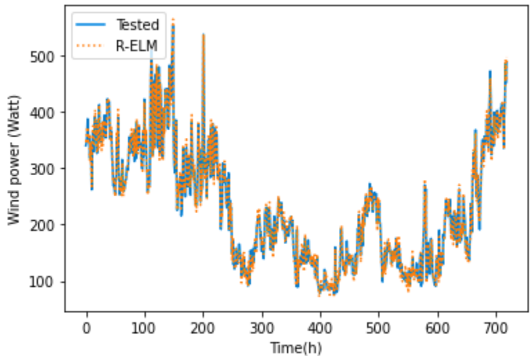

Figure 6. Wind power predicted by R-ELM in summer

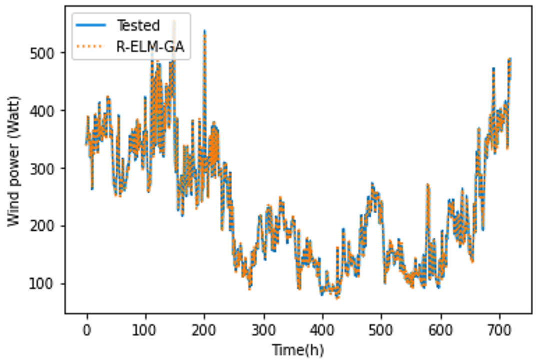

Figure 7. Wind power predicted by R-ELM-GA in summer

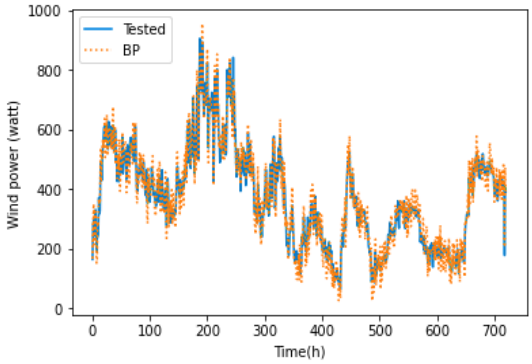

Figure 8. Wind power predicted by BP in winter

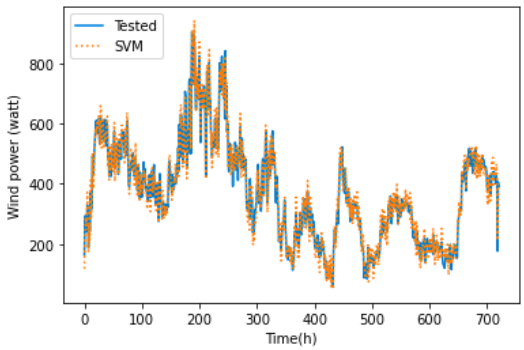

Figure 9. Wind power predicted by SVM in winter

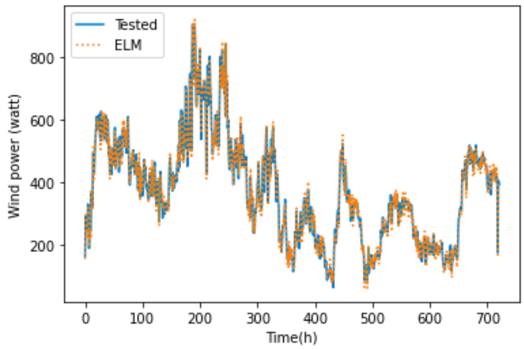

Figure 10. Wind power predicted by ELM in winter

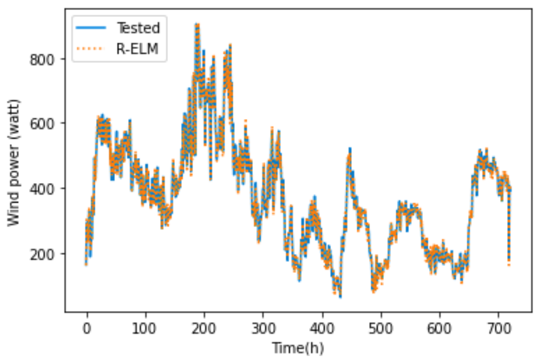

Figure 11. Wind power predicted R-ELM in winter

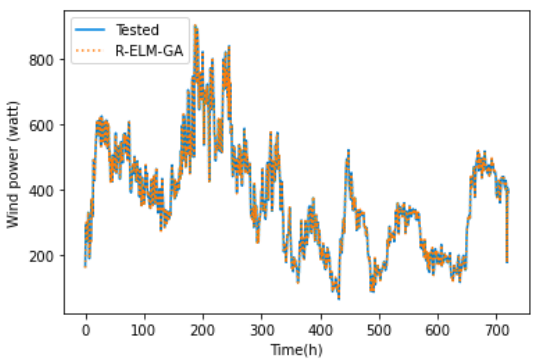

Figure 12. Wind power predicted by R-ELM-GA in winter

The five models' combined predictions for the summer and winter seasons are shown in Tables 1 and 2, respectively. The tables provide the time convergence of each technique in seconds and the MSE score, which may be determined as (17):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - O_i) \quad (17)$$

where the number of instances in the test set is n, the predictive output is O_i, and the measured output is y_i.

The results shown in Tables 1 and 2 highlighted the execution of the suggested R-ELM-GA method concerning the MSE error. In comparison to the other models, BP and SVM provided the largest MSE since they provided a considerable discrepancy between the test values and the forecast's outcome. It is about 0.8579 for BP and 0.7256 for SVM in the summer season. In contrast, MSE's ELM and R-ELM are about 0.1827 and 0.1853 respectively, which are even larger than the MSE's R-ELM-GA is about 0.1137.

For the winter season, the MSE is about 0.9251 for BP and about 0.8689 for SVM. Furthermore, the error of ELM and R-ELM are about 0.3486 and 0.1932 respectively. All these models produce larger errors than that of R-ELM-GA which is about 0.1573.

In addition, the biggest time convergence value is reached by BP and SVM which calls for a lengthy computing process with several iterations. On the other hand, ELM, R-ELM, and the proposed model give the lowest values. Although the proposed model uses GA to reduce the number of hidden nodes, it still gives a smaller convergence time. Given that the suggested R-ELM-GA approach offered comparably better forecasts than static models and required faster convergence, all these findings illustrated the adaptability of the method.

Table 1. Comparison of different models in the summer

Prediction method	MSE	Time convergence(s)
R-ELM-GA	0.1137	0.8153
R-ELM	0.1853	0.7283
ELM	0.2597	0.6324
SVM	0.7256	4.1527
BP	0.8759	5.1725

Table 2. Comparison of different models in the winter

Prediction method	MSE	Time convergence(s)
R-ELM-GA	0.1573	0.8582
R-ELM	0.1932	0.7591
ELM	0.3486	0.6816
SVM	0.8689	5.9872
BP	0.9251	6.2853

4. CONCLUSION

The operational safety of the electricity grid requires the need to provide wind energy as the most used RE source, but this is still very difficult due to the instability of wind speeds and their severe interruptions. That is why forecasting wind speed has become essential for the effective utilization of energy. In this regard, we have provided this article with a power forecasting model for the generation of wind energy using the R-ELM and GA, the so-called R-ELM-GA based on past wind speed values, the suggested model tried to forecast the next wind energy produced through the wind turbines. The GA was employed to choose the ideal network design, that is, the ideal number of hidden nodes, in the initial network of the R-ELM model. The simulation results highlighted the execution of the suggested R-ELM-GA algorithm as it has produced relatively better predictions than the other compared algorithms. It is a very fast, powerful, and active learning algorithm. As a result, we can deduce that the R-ELM-GA can be utilized very flexibly in the domain of wind power forecasting. In future works, we will focus on enhancing the proposed R-ELM-GA model by employing a twofold optimization strategy to select the number of hidden nodes in the complete model and the regularization parameter of R-ELM most advantageously.

REFERENCES

[1] M. Feroldi, P. A. Cremonez, C. D. J. de Oliveira, A. Estevam, T. W. Meier, and J. G. Teleken, "Oxidative stability of biodiesel blends derived from waste frying oils," *Acta Scientiarum. Technology*, vol. 39, no. 3, pp. 375-378, Jul. 2017, doi: 10.4025/actascitechnol.v39i3.29406.

[2] I. M. Wartana, N. P. Agustini, and S. Sreedharan, "Improved security and stability of grid connected the wind energy conversion system by unified power flow controller," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 27, no. 3, pp. 1151–1161, Sep. 2022, doi: 10.11591/ijeecs.v27.i3.pp1151-1161.

[3] P. Du, J. Wang, W. Yang, and T. Niu, "A novel hybrid model for short-term wind power forecasting," *Applied Soft Computing*, vol. 80, pp. 93–106, Jul. 2019, doi: 10.1016/j.asoc.2019.03.035.

[4] S. R. Moreno, R. G. da Silva, V. C. Mariani, and L. d. S. Coelho, "Multi-step wind speed forecasting based on hybrid multi-stage decomposition model and long short-term memory neural network," *Energy Conversion and Management*, vol. 213, p. 112869, Jun. 2020, doi: 10.1016/j.enconman.2020.112869.

[5] S. R. Salkuti, "Solving combined economic emission dispatch problem in wind integrated power systems," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 2, pp. 635-641, Feb. 2021, doi: 10.11591/ijeecs.v21.i2.pp635-641.

[6] P. Jiang, H. Yang, and J. Heng, "A hybrid forecasting system based on fuzzy time series and multi-objective optimization for wind speed forecasting," *Applied Energy*, vol. 235, pp. 786–801, Feb. 2019, doi: 10.1016/j.apenergy.2018.11.012.
[7] A. Lahouar and J. B. H. Slama, "Hour-ahead wind power forecast based on random forests," *Renewable Energy*, vol. 109, pp. 529–541, Aug. 2017, doi: 10.1016/j.renene.2017.03.064.
[8] Y. Hao and C. Tian, "The study and application of a novel hybrid system for air quality early-warning," *Applied Soft Computing*, vol. 74, pp. 729–746, Jan. 2019, doi: 10.1016/j.asoc.2018.09.005.
[9] Y. Wang, J. Wang, and X. Wei, "A hybrid wind speed forecasting model based on phase space reconstruction theory and Markov model: A case study of wind farms in northwest China," *Energy*, vol. 91, pp. 556–572, Nov. 2015, doi: 10.1016/j.energy.2015.08.039.
[10] K. Herbandono and C. S. A. Nandar, "Adaptive robust control design to enhance smart grid power system stabilization using wind characteristics in Indonesia," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 12, no. 4, pp. 2182–2190, Dec. 2021, doi: 10.11591/ijpeds.v12.i4.pp2182-2190.
[11] J. Zhao, Z.-H. Guo, Z.-Y. Su, Z.-Y. Zhao, X. Xiao, and F. Liu, "An improved multi-step forecasting model based on WRF ensembles and creative fuzzy systems for wind speed," *Applied Energy*, vol. 162, pp. 808–826, Jan. 2016, doi: 10.1016/j.apenergy.2015.10.145.
[12] G. Fung and O. L. Mangasarian, "Proximal support vector machine classifiers," in *Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining*, Aug. 2001, pp. 77–86, doi: 10.1145/502512.502527.
[13] W. Yang, J. Wang, T. Niu, and P. Du, "A hybrid forecasting system based on a dual decomposition strategy and multi-objective optimization for electricity price forecasting," *Applied Energy*, vol. 235, pp. 1205–1225, Feb. 2019, doi: 10.1016/j.apenergy.2018.11.034.
[14] G. Li and J. Shi, "On comparing three artificial neural networks for wind speed forecasting," *Applied Energy*, vol. 87, no. 7, pp. 2313–2320, Jul. 2010, doi: 10.1016/j.apenergy.2009.12.013.
[15] A. Meng, J. Ge, H. Yin, and S. Chen, "Wind speed forecasting based on wavelet packet decomposition and artificial neural networks trained by crisscross optimization algorithm," *Energy Conversion and Management*, vol. 114, pp. 75–88, Apr. 2016, doi: 10.1016/j.enconman.2016.02.013.
[16] S. A. P. Kani and M. M. Ardehali, "Very short-term wind speed prediction: A new artificial neural network–Markov chain model," *Energy Conversion and Management*, vol. 52, no. 1, pp. 738–745, Jan. 2011, doi: 10.1016/j.enconman.2010.07.053.
[17] L. Lei, "Wavelet Neural Network Prediction Method of Stock Price Trend Based on Rough Set Attribute Reduction," *Applied Soft Computing*, vol. 62, pp. 923–932, Jan. 2018, doi: 10.1016/j.asoc.2017.09.029.
[18] S. Sun, H. Qiao, Y. Wei, and S. Wang, "A new dynamic integrated approach for wind speed forecasting," *Applied Energy*, vol. 197, pp. 151–162, Jul. 2017, doi: 10.1016/j.apenergy.2017.04.008.
[19] D. El Bourakadi, A. Yahyaouy, and J. Boumhidi, "Extreme Learning Machine Based Multi-Agent System for Microgrid Energy Management," in *Advanced Intelligent Systems for Sustainable Development (AI2SD'2018)*, 2019, pp. 30–39, doi: 10.1007/978-3-030-12065-8_4.
[20] H. Elaimani, A. Essadki, N. Elmouhi, and F. Bahja, "Adaptive doubly fed induction generator's control driven wind turbine using luenberger observer optimized by genetic algorithm," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 1, pp. 120–132, Jan. 2022, doi: 10.11591/ijeecs.v29.i1.pp120-132.
[21] R. U. K. Nadya, A. N. Ahmed, A. A. Borhana, N. A. Mardhiah, A. El-Shafie, and A. El-Shafie, "Daily predictions of solar radiation utilizing genetic programming techniques," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 19, no. 2, pp. 900-905, Aug. 2020, doi: 10.11591/ijeecs.v19.i2.pp900-905.
[22] K. Andal C. and J. R., "Improved GA based power and cost management system in a grid-associated PV-wind system," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 12, no. 4, pp. 2531-2544, Dec. 2021, doi: 10.11591/ijpeds.v12.i4.pp2531-2544.
[23] N. Elmouhi, A. Essadki, and H. Elaimani, "Robust control of wind turbine based on doubly-fed induction generator optimized by genetic algorithm," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 13, no. 2, pp. 674-688, Jun. 2022, doi: 10.11591/ijpeds.v13.i2.pp674-688.
[24] R. Malemnganbi and B. A. Shimray, "An integrated multiple layer perceptron-genetic algorithm decision support system for photovoltaic power plant site selection," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 2, pp. 1965-1972, Apr. 2022, doi: 10.11591/ijece.v12i2.pp1965-1972.
[25] X. Wang, C. Wang, and Q. Li, "Short-term Wind Power Prediction Using GA-ELM," *The Open Electrical & Electronic Engineering Journal*, vol. 11, no. 1, pp. 48–56, Feb. 2017, doi: 10.2174/1874129001711010048.
[26] V. Maniezzo, "Genetic evolution of the topology and weight distribution of neural networks," *IEEE Transactions on Neural Networks*, vol. 5, no. 1, pp. 39–53, 1994, doi: 10.1109/72.265959.
[27] M. El jaadi, T. Haidi, and D. Bouabdallaoui, "Particle swarm optimization for the optimal layout of wind turbines inside a wind farm," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 3, pp. 1260-1269, Sep. 2023, doi: 10.11591/ijai.v12.i3.pp1260-1269.
[28] R. Rahmani, R. Yusof, M. Seyedmahmoudian, and S. Mekhilef, "Hybrid technique of ant colony and particle swarm optimization for short term wind energy forecasting," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 123, pp. 163–170, Dec. 2013, doi: 10.1016/j.jweia.2013.10.004.
[29] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: Theory and applications," *Neurocomputing*, vol. 70, no. 1–3, pp. 489–501, Dec. 2006, doi: 10.1016/j.neucom.2005.12.126.
[30] D. El Bourakadi, A. Yahyaouy, and J. Boumhidi, "Multi-agent system based on the fuzzy control and extreme learning machine for intelligent management in hybrid energy system," in *2017 Intelligent Systems and Computer Vision (ISCV)*, Apr. 2017, pp. 1–6, doi: 10.1109/ISACV.2017.8054922.
[31] W. Deng, Q. Zheng, and L. Chen, "Regularized Extreme Learning Machine," in *2009 IEEE Symposium on Computational Intelligence and Data Mining*, Mar. 2009, pp. 389–395, doi: 10.1109/CIDM.2009.4938676.
[32] D. El Bourakadi, A. Yahyaouy, and J. Boumhidi, "Multi-Agent System Based on the Extreme Learning Machine and Fuzzy Control for Intelligent Energy Management in Microgrid," *Journal of Intelligent Systems*, vol. 29, no. 1, pp. 877–893, Dec. 2019, doi: 10.1515/jisys-2018-0125.
[33] D. El Bourakadi, A. Yahyaouy, and J. Boumhidi, "Improved extreme learning machine with AutoEncoder and particle swarm optimization for short-term wind power prediction," *Neural Computing and Applications*, vol. 34, no. 6, pp. 4643–4659, Mar. 2022, doi: 10.1007/s00521-021-06619-x.
[34] D. EL Bourakadi, A. Yahyaouy, and J. Boumhidi, "Multi-agent system based sequential energy management strategy for Micro-Grid using optimal weighted regularized extreme learning machine and decision tree," *Intelligent Decision Technologies*, vol. 13,

no. 4, pp. 479–494, Feb. 2020, doi: 10.3233/IDT-190003.
[35] M. Liu, Z. Cao, J. Zhang, L. Wang, C. Huang, and X. Luo, "Short-term wind speed forecasting based on the Jaya-SVM model," *International Journal of Electrical Power & Energy Systems*, vol. 121, p. 106056, Oct. 2020, doi: 10.1016/j.ijepes.2020.106056.

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