International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Application of Novel Strategy Based on Deep Learning for Forecasting Wind Speed

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Submitted: 07/10/2023 **Revised**: 25/11/2023 **Accepted**: 05/12/2023

Abstract: In several fields, including aviation, environmental management, and the production of energy from renewable sources, exact wind speed forecast is important. The complexity and nonlinearity of the data on wind speed provide difficulties for conventional prediction techniques frequently. In this study, a unique method for improving predictions of wind speed is put forth. It combines the optimization of Satin Bowerbird (SBO) algorithm with the Backpropagation Neural Network (BPNN). The BPNN is ideal for modeling wind speed patterns because it can capture nonlinear interactions. However, the conventional BPNN training procedure is prone to become stuck in local optima, producing predictions that are less than ideal. The SBO technique is used to modify the BPNN characteristics in order to get around this restriction. The performance of the suggested strategy is examined in this study using wind speed information. The suggested SBO-BPNN methodology has the potential to increase the accuracy of wind speed predictions, allowing for better scheduling and making choices in a variety of wind energy-dependent businesses. Future studies should examine how well this model works for similar prediction-related tasks like estimating wind power or predicting wind direction.

Keywords: *Wind speed, wind power, renewable energy, prediction, Satin Bowerbird optimization (SBO), Backpropagation Neural Network (BPNN)*

1. Introduction

Wind speed forecasting is an essential component of modern meteorological science, with applications ranging from aviation safety to renewable energy optimization. We can improve decision-making, safeguard people and property, and promote sustainable development by forecasting wind behavior. Wind, a renewable and natural energy source, is a key component in the generation of electricity by wind turbines [1]. Wind energy is regarded as a clean, green, and environmentally friendly energy source because it is renewable and emits no greenhouse gases while in use. The speed and direction of the wind have a significant impact on the effectiveness and efficiency of wind energy generation [2]. Therefore, for wind energy companies to estimate and manage power production effectively, accurate wind speed prediction becomes crucial. The process of predicting wind speed is difficult. Numerous factors, such as air pressure variations, the Coriolis Effect, temperature gradients, geographical elements like terrain and water bodies, and more complex climate systems all have an impact on wind, an atmospheric phenomenon. Accurate wind speed prediction is difficult due to these interactions [3]. Deterministic methods, which offer a single result based on particular initial conditions, were used for wind speed prediction. However, the inherent uncertainty in predicting wind speed is frequently missed by these methods. Modern wind speed forecasting methods have progressively used machine learning and artificial intelligence techniques as computational power and data availability have increased. In order to predict future wind speeds, these methods which may include but are not limited to neural networks, random forests, and gradient boosting capture patterns in historical data. Time-series forecasting is one well-liked method, for instance [5].

Time-series models forecast future values based on historical data points. This method has a number of advantages, one of which is that it is capable of capturing the temporal dependencies that are present in wind speed data. For this purpose, it is common practice to employ models such as the seasonal decomposition of time series (STL), the long short term memory (LSTM) , and the autoregressive integrated moving average (ARIMA) models. Another category of forecasting techniques focuses on identifying the built-in statistical characteristics of the data [5]. The Weibull distribution, which is widely used to model wind speed data, is one example of a distribution that these techniques frequently assume the data will follow. This distribution accurately captures the skewness and variability of wind speed. Models made of physical objects are used in another technique. In order to

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forecast wind speed, these models simulate the physics of atmospheric flow and the interactions between the atmosphere and the surface of the Earth [6]. Physical models used for predicting wind speed include numerical weather prediction (NWP) models. While each of these approaches has advantages, they also have drawbacks. In the event that the underlying assumptions are incorrect, time-series and statistical models may not work. Physical models can be computationally demanding and require a lot of precise input data despite being more thorough. As a result, hybrid models which combine the advantages of both of these approaches are growing in acceptance [7].

We suggest a novel approach to enhance the wind speed prediction. It combines the Satin Bowerbird Optimisation (SBO) algorithm with the Backpropagation Neural Network (BPNN). The BPNN's ability to capture nonlinear interactions makes it ideal for modeling wind speed patterns.

The rest of the paper organizations are arranged according to: related work is discussed in part 2, the method is presented in part 3, the results and discussion is describes in part 4, and the conclusion of the paper covered in part 5.

2. Related Works

Machine learning techniques were utilized to predict a certain amount of wind power using daily wind speed information. In particular, projections of the given wind speed estimates were made by using classification algorithms. The hourly wind speed data collection was used to generate values for the daily mean wind speed, and the SD as well as the daily wind speed was used to model the daily total wind power [8]. Study [9] proposed a novel dynamic integrated technique for wind speed forecasting that integrates an optimized core vector regression (OCVR), and kernel principal component analysis (KPCA) system utilizing phase space reconstruction (PSR). Article [10] proposed a better rendition of the “Radial Basis Function (RBF) Neural Network”, augmented by a system of error feedback, especially for quick wind speed or wind power forecasts. His original strategy entails adding a parameter initialization step and including a form parameter into each hidden neuron's Gaussian basis function. These changes serve two purposes: they improve the precision and efficacy of the forecasting system's convergence and enable the algorithm to search for more ideal beginning values for both the center and SD.

Study [11] recommended a “PCFS that combines point forecasting”, interval forecasting, and efficient sub-model selection. Additionally, three experiments and three analyses were carried out using two datasets from the Chinese Shandong Peninsula. Article [12] presented a “Jaya-SVM method for predicting short-term wind speed”. The Jaya optimization procedure, which makes utilize the most representative elements of the input information, is used to optimize the "hyper-parameters" of the SVM in the manner described. Paper [13] described many techniques for predicting wind speed. When wind speed is forecasted in huge multi-steps, the performance evaluations of the two boosting and forecasting algorithms are studied. Study [14] developed a multi-variable stacked LSTM system for predicting immediate wind speed. For real-time wind projections, this system supports the ingestion of several meteorological inputs. The suggested MSLSTM model takes data at various scales from previous parameters, aids the network in enabling a more complicated representation of the wind speed data collected over time, and simultaneously guards against over-fitting. NWP wind speed adjustment using GRUNNs as a foundation has been proposed for short-term wind power forecasts. The first stage is to analyze the wind speed characteristic of NWP and extract the SD of NWP weights according to the error in wind speed for the NWP time series of sped of wind. To fix the NWP wind speed error, a unidirectional GRUNNs-based error correction system is then provided [15].

3. Method

3.1 BPNN

We briefly describe the BP neural network in this part because it serves as the study's baseline technique. In a BP neural network, each neuron uses a nonlinear transfer function in order to compute the internal the input vector's product and the weight vector and arrive at a scalar result. This allows the neuron to arrive at a scalar result. Because of this, the neuron is able to determine a scalar value. This step must be completed before moving on to the next step, which will allow the scalar value to be calculated. The three layers of this particular network are the input layer, the output layer and the hidden layer. The visible layer is the layer of input. The input layer is the user is actually looking at. The five input layer nodes stand in for the five days and hour average wind speed values from the past. Our decision to use an input layer with five nodes is supported by thorough testing, which shows that in this situation, the forecasting outcome is significantly better than in different circumstances. The daily wind speed forecasting value is the only node in the output. As is well known, the neural network's robustness is impacted by the hidden layer.

We employ the Hecht–Nelson approach finding a hidden layer's node number in order to produce more accurate prediction results. According to this method, while The input layer's node value is n, while the hidden layer's node value is 2n + 1. The training of a BP network with n input neurons, $2n + 1$ hidden neurons, and a single output neuron looks like this. We use a normalized approach to handle the values of the input and output before training the network to guarantee accurate forecasts.

$Y' = \{Y'j\} = 2 \times \frac{Yj - Yjmin}{Yjmax - Yjmin} - 1, j = 1,2, \ldots, mY' \subset [1,1]$ (1)

Where $Yjmin$ and $Yjmax$ represent the input array's minimum and maximum values, respectively, while Yj stands for each vector's actual value.

Stage 1: Determine the outputs for each hidden layer node.

$x_i = l(\sum_j U_{ij} Y_j + p_i) = l(net_i)(j = 1, \ldots, n; i = 1, \ldots, 2m + 1)$ (2)

$$net_i = U_{ji} x_i + p_i (i = 1, \ldots, 2m + 1) \quad (3)$$

p_i Indicates the partiality of the neuron i, x_i signifies output from the node in the hidden layer i, and f is the initiation coefficient of a node, which is typically a function of sigmoid. Whereas net_i represents the activation value of node j, U_{ji} represents the weight of the link from inputs node j to hidden node i, and x_i represents the output of the hidden layer node i.

Stage 2: Compute the neural network's output information.

$$0_1 = l_0(U_{qi} x_i + p_q)(i = 1, \ldots, 2m + 1) \quad (4)$$

"U_{qi}" stands for the link weight from "hidden node" to "output node 0," "p_q" refers to the bias, "0_1" is the data that is the network's output and "l_0" is the activating the output layer node's function. These terms are used in the context of this particular illustration.

Stage 3: Reduce the overall error E using the training procedure.

$$A = \frac{1}{2} \sum (Q_1 - K_d)^2 \quad (5)$$

$K_d$ids the real output

3.2 Satin bowerbird optimization

The SBO begins by creating a population in a random manner. It stands for a group of bower positions, each of which has a D-dimensional vector. The algorithm requires improving the vectors' parameters. Each bower's fitness (Fik_j) is determined using the following equation:

$$Fik_j = \begin{cases} \frac{1}{1 + e(V_j)} e(V_j) \geq 0 \\ 1 + |e(V_j)| e(V_j) \geq 0 \end{cases} \quad (6)$$

Where $e(V_j)$ denotes the bower's cost.

The probability of each bower is then determined using Equation 2 and NB as the number of bowers:

$$O_j = \frac{Fit_j}{\sum_{m=1}^{M_A} Fit_j} \quad (7)$$

Bowers are ranked in order of quality based on their fitness, with the most fit one being chosen. To stay current, the rest of the population attempts to imitate the best one. This is accomplished by utilizing Equations 8 and 9.

$$V_{jl}^{new} = V_{jl}^{old} + \lambda_l \left[\left(\frac{V_{il} + V_{best,l}}{2} \right) - V_{jl}^{old} \right] \quad (8)$$

$$\lambda_l = \frac{b}{1 + O_i} \quad (9)$$

Where$\lambda_l$refers to step magnitude and a denotes the biggest step size. The roulette wheel technique also yields i. The mutation must then proceed to be put into practice. To that goal, V_{jl} undergoes a series of unpredictable events with a specified frequency. An assumption of a normal distribution (N) is made based on Equations (10) and (11).

$$V_{jl}^{new} \sim M(V_{jl}^{old}, \sigma^2) = V_{jl}^{old} + (\sigma M(0,1)) \quad (10)$$

$$\sigma = y(Var_{max} - Var_{min}) \quad (11)$$

Where 2 is the variance factor, Varmin, Varmax, and z all represent the relative (%) differences between these two parameters, with Varmin and Varmax designating the lower and upper bounds. The algorithm then sorts existing bowers and finds the best one to use as the solution.

3.3 Hybrid Satin Bowerbird optimized BPNN

A neural network architecture that incorporates components from both the Satin bowerbird optimization algorithm and a BPNN is likely referred to as a hybrid Satin bowerbird optimized BPNN. This could entail optimizing the weights and neural network biases while using the Satin Bowerbird optimization method, potentially enhancing its performance in terms of accuracy or convergence speed. It's important to note that the context and objectives of the problem being addressed will determine the specifics of this hybrid approach' implementation. It might be a fresh research hypothesis or a method that has been put forth for a particular use. To offer more thorough insights, more information about the particular strategy or research paper would be necessary..

4. Result and Discussion

a. Numerical demonstrations

The The data on wind speed from China's Changma wind farm (Zhang et al., (2020)) is used as a model to evaluate the technique's ability for wind speed prediction in a real-world wind field. Every wind field collects a wind speed reading every 20 minutes, with a maximum per day of 144 readings. 4460 four wind speed observations from 31 days of wind speed data were used in this inquiry. The wind farm's 31-day wind speed variance. The wind speed varies greatly, with a greatest speed of the wind of approximately 34 m/s and a lowest speed of wind of 0 m/s. The wind speed for 31 days values given in this study were used in the investigations presented. This investigation was presented in Matlab.

The existing methods are “improved radical basis function neutral network-error feedback (IRBFNN-EF)” [10], “a

Jaya algorithm-based Support vector machine (Jaya-SVM)" [12], and the gated recurrent unit neural network (GRUNN) [15] compared with proposed (SBO-BPNN). The parameters like "Mean error (AE), Mean absolute error (MAE), Mean square error (MSE), and Mean absolute percentage error (MAPE)", Where "true positives (S_1), false positives (P_1), true negatives (S_2), and false negatives (P_2)".

The average forecast error (AE) is equal to n times the forecasted results as in Equation (12). Figure 1 depicts the Average error (AE) for existing IRBFNN-EF, Jaya-SVM, and GRUNN is 0.35, 0.28, and 0.21 and our proposed approach is 0.15. It shows that our proposed technique has low average error than existing methods

$$AE = \frac{1}{M}\sum_{m=1}^{M}(z_m - \hat{z}_m) \qquad (12)$$

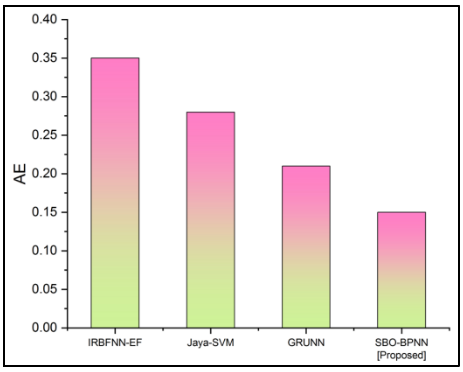

Fig 1: Average error (AE)

The MAE refers to the n-times average absolute forecast error the predicted outcomes Equation 13. Figure 2 displays MAE for existing IRBFNN-EF, Jaya-SVM and GRUNN as 0.79, 0.45, and 0.87 and our proposed approach is 0.33. The existing has high error than the proposed approach.

$$MAE = \frac{1}{M}\sum_{m=1}^{M}|z_m - \hat{z}_m| \qquad (13)$$

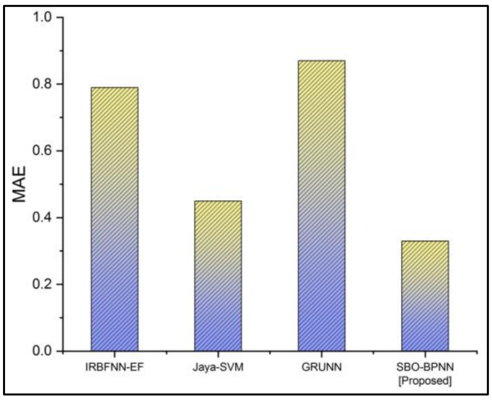

Fig 2: Mean absolute error (MAE)

MSE, which measures the average of prediction error squares, helps assess how the predicted system has changed as in Equation 13. Figure 3 depicts MSE for existing IRBFNN-EF, Jaya-SVM and GRUNN is 1.47, 1.25 and 1.25 and our proposed approach is 0.21.

$$MSE = \frac{1}{M}\sum_{m=1}^{M}(z_m - \hat{z}_m)^2 \qquad (14)$$

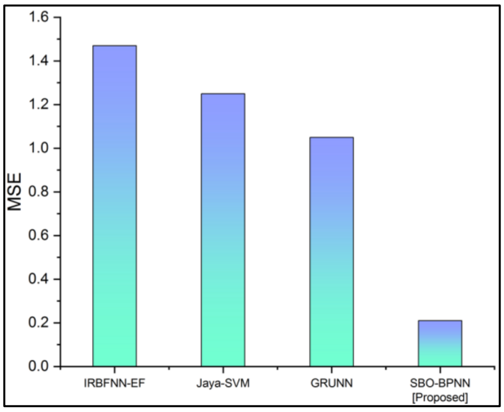

Fig 3: Mean square error (MSE)

A statistician's performance evaluation and comparison tool called MAPE measures the predict method's accuracy as in Equation 14. Figure 4 displays MAPE for existing IRBFNN-EF, Jaya-SVM and GRUNN is 57.78, 44.35, and 37.59 and our proposed approach is 21.93. It proves that, in comparison to other methods currently in use, our methodology has less error.

$$MAPE = \frac{1}{M}\sum_{m=1}^{M}\left|\frac{z_m - \hat{z}_m}{z_m}\right| \times 100\% \qquad (15)$$

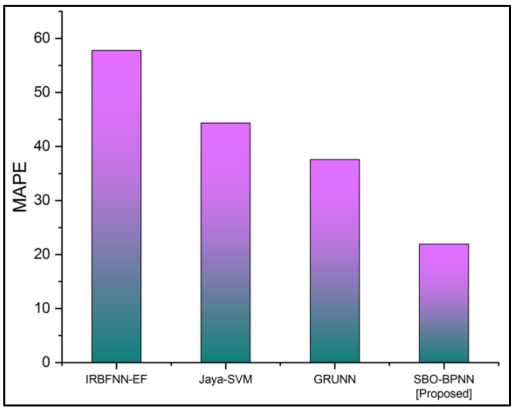

Fig 4: Mean absolute percentage error (MAPE)

The degree to which a calculation or estimate matches the real or genuine value is known as accuracy. It is an important statistic in Equation 16's evaluation of predictive models. Figure 5 shows the comparison of accuracy for existing IRBFNN-EF, Jaya-SVM and GRUNN is 85%, 78%, and 83%, and our proposed method SBO-BPNN has 97%. This indicates that the approach we have suggested is more precise in predicting the wind speed than the existing techniques.

$$Accuracy = \frac{S_2 + S_1}{S_2 + S_1 + P_2 + P_1} \qquad (16)$$

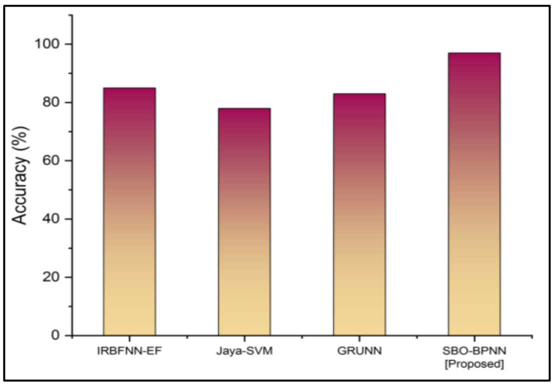

Fig 5: Accuracy

5. Conclusion

In this article, we suggested an innovative method to improve wind speed prediction. The Satin Bowerbird optimization (SBO) algorithm and the Backpropagation Neural Network (BPNN) are hybridized in this study. For simulating fluctuations in wind velocity, the BPNN is a perfect fit since it can describe nonlinear interactions. The results showed that our suggested strategy performed well based on a range of criteria, including AE, AE, MSE, MAPE, and accuracy, which were 0.15, 0.33, 0.21, 21.93, and 97%. Using more current iterations of the SBO could help find a more effective solution. Further research into possible future works may be conducted by using this concept and using other comparing algorithms.

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