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Wind speed prediction for hybrid-based energy integration

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Abstract. Wind energy has been widely explored and utilized as a renewable energy source. The integration of wind energy with other energy sources has been going well and to strengthen the current energy. However, this paper only discusses wind speed prediction in renewable energy by integrating hybrid-based energy. Combination of systems with the Successive model Variational Mode Decomposition uses the Least Squares Support Vector Machines (LSSVM) model to obtain parts of the system with new variants. This study proposes a hybrid model for short-term Water Supply Footprint (WSF) that takes into account the suitability of the LSSVM model for average data size and computational resources with an improved Quantum-Behaved Particle Swarm Optimization (QPSO) algorithm to optimize its parameters, with an Long Short-Term Memory (LSTM) network to model irregular sequences, and the advantages of the Sequential VMD (SVMD) algorithm. This is to produce the predicted intrinsic mode and the error sequence is taken as the predicted final output wind speed result. For wind speed prediction, the assets in the proposed model obtained an Root Mean Squared Error (RMSE) of 0.703, Mean Absolute Error (MAE) of 0.512, mean absolute percentage error (MAPE) of 5.9%, R^2 of 0.796, and a correlation coefficient of 0.892.

Keywords: Wind speed prediction, Renewable energy, RMSE, MAE, MAPE, R^2.

1 Introduction

Current technological developments and advances mean that the use of fossil fuels is decreasing because it impacts air and environmental pollution [1–3]. As a substitute for the energy shortage, the transition to renewable energy is a form of public concern for maintaining green energy [4–6]. Wind speed in tropical areas has good potential to be used as a source of green energy, especially for turning wind turbines, because it has high efficiency without causing pollution [7, 8]. The change in kinetic energy produced by wind turbines into electrical energy is easy to operate and cheap [9, 10].

The use of wind power has several obstacles because wind speed always fluctuates, thus affecting the power speed the wind generates when the turbine rotates [11]. This wind power cannot be for the future, but wind energy can be stored in batteries which can be used as a source of electricity at certain times [12]. Managers always think about how to balance producers and users to ensure the continuous use of wind energy [13, 14].

Wind power prediction for serving the demand for electrical energy is a consideration model for minimal operational costs but has optimal benefits [15]. The obstacles that are always experienced when integrating a network system where fluctuating wind speeds and fairly high operational costs will result in uncertainty and are difficult to predict as well as the possibility of damage [16]. Therefore, integration for predicting accurate and reliable wind speed is important to minimize operational costs.

The wind speed prediction strategy consists of an initial forecast to determine the potential as a wind turbine driving source which is used as a benchmark to determine the capacity of the turbine to be installed [17, 18]. The next strategy is a direct forecasting of best wind speed conditions at the research location. These two strategies are the best choices that are theoretically and practically acceptable for predicting the potential of wind speed as a renewable

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energy source [19, 20]. However, this can be seen if there are no other wind energy sources so that potential predictions can be made on the downstream side of the wind energy source. Wind predictions are generally carried out every 30 min to 6 h, even up to daily calculations, so this is a consideration in predicting the potential of wind speed as a renewable energy source [21, 22].

In some countries, power plant development is focused on low-emission green energy, such as wind energy [23]. Therefore, this study focuses on the prediction of hybrid power plants based on the development of integrated technology, namely short-term wind speed prediction by combining advances in Artificial Intelligence (AI) technology. The combination of systems with the Successive model Variational Mode Decomposition uses the Least Squares Support Vector Machines (LSSVM) model to obtain a part of the system with a new variant. The proposed new variant is a combination of several parameters related to wind speed and training conducted to see the success of the combined system. Furthermore, the trend of the error sequence was obtained from the proposed mode and data speed. The wind is modeled by Long Short-Term Memory (LSTM) to further improve the accuracy and maintain stable performance. This results in the predicted intrinsic modes and the error sequence is taken to produce the final predicted output wind speed.

2 Literature review

For prediction models, accurate wind speed and wind power are required. In academics and industry, research related to wind speed was conducted [24]. Wind speed prediction has been done using physical methods, statistical methods, AI-based methods, and hybrid methods. For the physics-based method, Numerical Weather Prediction (NWP) and the utilization of weather variables [25]. Using the proposed Sequence Transfer Correction Algorithm (STCA) for NWP wind speed sequences which is a new forecasting method.

The statistical model is an Autoregressive Moving Average (ARMA) model that utilizes the method using wind speed and direction forecasting by separating wind speed into lateral and longitudinal space, forecasting each individually, and combining them to get the final forecast [26]. Another model used is Autoregressive Moving Average with Extra Input (ARMAX) to produce superior performance compared to other models. The weakness of the statistical model is that its structure is simple, its computation time is fast, and its interpretation ability is strong, but it takes longer to run so the forecast accuracy decreases. As a result, the statistical method will fail when associated with nonlinear relationships in the time series. The statistical method is more suitable for geostationary time series than non-stationary series, and real wind data is mostly non-stationary [27, 28].

AI-based algorithm models utilize machine learning and deep learning algorithms, so they have the best accuracy and strong capabilities in handling nonlinear and nonstationary data for wind forecasting applications, such as those used in Artificial Neural Network (ANN) models, Eukaryotic Linear Motif (ELM) models, etc. [29]. For self-supervised learning and non-linear mapping, ANN models are used for Water Supply Footprint (WSF) applications. However, ANN models can easily get trapped in local minima during training because defining important parameters such as learning rate, number of iterations, and trapping criteria is usually difficult.

The LSSVM algorithm model is a refinement of SVM which handles linear equations, but this method has been widely used in WSF. However, LSSVM relies on two important hyperparameters that greatly affect the overall prediction performance [30]. These two hyper parameters, known as the regularization parameter and the kernel parameter, must be chosen carefully to avoid overfitting or under fitting [31]. A new proposal for the PSO algorithm to obtain optimal parameters of LSSVM trained using a dataset collected from wind farms in Indonesia. The short-term WSF method uses an improved PSO method on a combination of persistence methods, Radial Basis Functions (RBFs), and neural networks. Learning methods in the subcategory of AI-based approaches have also been widely used for wind speed forecasting, namely Recurrent Neural Networks (RNNs), Nerve Convolutional (CNN), and LSTM [32, 33].

Wind speed prediction with RNN based on Wind Speed and Turbulence Intensity is presented. The proposed scheme shows superior performance compared to other machine learning methods, but the problem related to the relationship between turbulence intensity and performance at different time intervals is not addressed. Although the results have been obtained, the results show that the accuracy can be further improved by increasing the number of feature maps and the number of neurons by using more hardware resources. The LSTM model is implemented to analyze the Primary Data Analysis (PDA) and is first used to reduce the dimensionality of meteorological data the Differential Evolution (DE) algorithm is applied to generate optimized values of the LSTM hyperparameters such as learning rate, number of hidden layer nodes, and batch size [34]. Overall, the advantages of deep learning models become more apparent when there is a large supply of data and plenty of computing resources.

The Empirical Mode Decomposition (EMD) model is used for WSF, decomposition Empirical Ensemble Mode (EEMD), and Decomposition Variation Mode (VMD). Method decomposition EMD and EEMD-based algorithms have been shown to produce moderate accuracy improvements. However, due to the aliasing phenomenon that occurs in EMD and the high prevalence of noise in the EEMD residuals, the accuracy improvements are limited. Therefore, SVMD is a better alternative for parsing time series data such as wind speed [35].

This study proposes a hybrid model for short-term WSF that takes into account the suitability of the LSSVM model for average data size and computational resources with an improved Quantum-Behaved Particle Swarm Optimization (QPSO) algorithm to optimize its parameters, with an LSTM network to model irregular sequences, and the advantages of the SVMD decomposition algorithm. Compared with other techniques, this work is novel because it is the first work that attempts to use the enhanced QPSO algorithm based on the principle of the transposon operator to optimize LSSVM parameters.

3 Methodology

3.1 SVMD model

The VMD model is a mathematical model that utilizes a time series of signals and K sub-signals in a non-recursive manner [36]. The time series used is independent of the sample rate and interference. Taking sub-signal K when the decomposition process begins will result in low K as a duplicate mode and high K will be at the mixed mode value so that the selection of inappropriate K will result in a decrease in algorithm performance and this results in a decrease in wind speed prediction results. The VMD model that has been presented aims to reduce the degradation of wind speed performance, so a model is needed to overcome this using the SVMD method, where in this model the K value will be extracted first before being used to produce the expected mode spectrum [37, 38].

The SVMD model assumes that the original signal is decomposed into two signals, namely the original signal and the residual signal, where the residual signal is also assumed to be a component, namely the sum of the previous mode and the original signal to be processed [39, 40]. The extracted original decomposition signal gives values that are around the center frequency which is the main criterion in the VMD model, while the spectral overlap is minimal and other residual signals are minimized for the reconstruction of existing modes and other residual signals [41]. The SVMD model algorithm is shown in Figure 1.

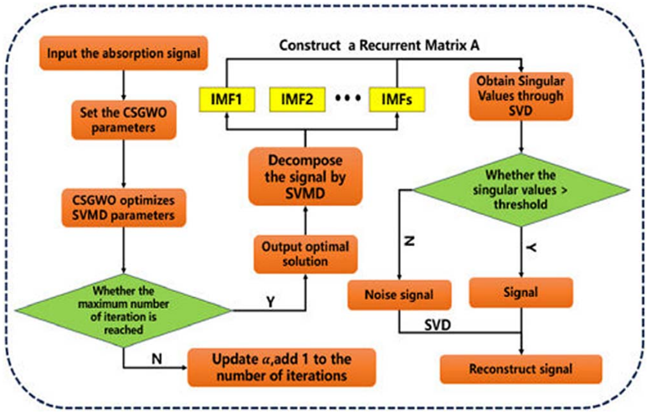

Fig. 1. Flowchart of the SVMD model.

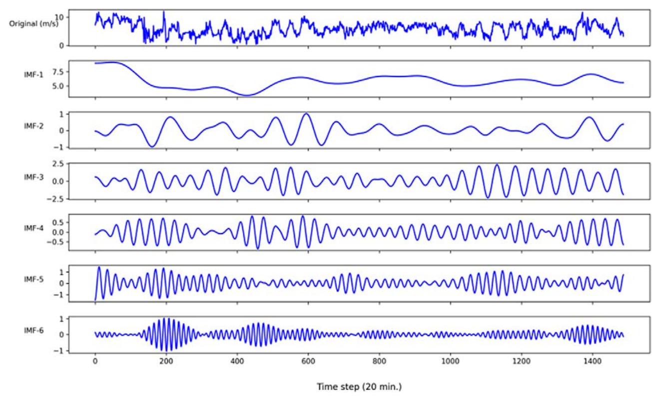

Fig. 2. Original wind speed and SVMD mode.

3.2 LSSVM model

The LSSVM model provides a better SVM model by utilizing least squares for efficient classification patterns and regression inputs and is used to generate linear optimization of the original signal. SVM has the advantage of learning from sophisticated patterns in the data set given by the Kernel function [42]. However, big data learning cannot execute it. The LSSVM model can execute big data by transforming inequality into controlled equality for complex linear optimization and expected function convergence [43]. The original wind speed and SVMD model are shown in Figure 2.

The LSSVM model maintains the trade-off that a large error penalty will cause the model to overfit the data patterns and data noise to produce the worst generalization model ability. For small values, the model will underfit, meaning the model fails to learn patterns from the given training set.

3.3 QPSO model

The QPSO model works on a new Particle Group Optimization (PSO) by simulating the quantum mechanics of particles. This model will affect the position of the delta model particles around it by utilizing the best position to improve the global search. The movement of QPSO particles in spinless quantum space by utilizing the estimated probability density function to determine its optimal point [44]. The first PSO for particle initialization iteratively produces the optimal solution of the particle, so that the evolution and mutation consisting of position and velocity vectors can be determined. The PSO model is computationally easier, but cannot be applied to complex multimodels. The QPSO model has an impact on the performance of the algorithm because each particle will affect the average population of the final solution and harm all large particles. The development of the QPSO model to find the optimal parameters on LSSVM by building a group of data for breeding and application to obtain various particles on long-term memory pool (LSTM) developed from the RNN model to overcome vanishing gradients. The LSTM unit consists of a cell, an input gate, an output gate, and a forget gate. All of these gates act as controllers of information entering and leaving the cell, while the forget gate acts as a selector of previous condition information to be forwarded and sets a value of zero or one.

3.4 Data set

The LSTM model is a deviation model between the original mode number and the original wind speed [45]. This model can handle vanishing and exploding gradients, making the LSTM model more suitable for non-linear and non-stationary error performance (Fig. 3).

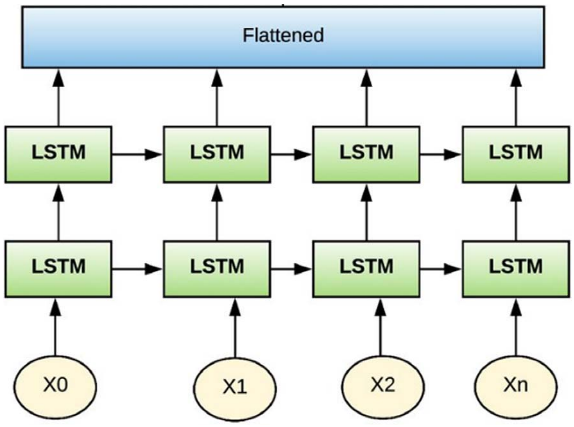

Fig. 3. LSTM used for modeling.

The dataset collection in this study was obtained from data from the *Meteorology, Climatology, and Geophysics Agency* (MCGA) of Medan City located at 3°27′–3°47′ North Latitude and 98°35′–98°44′ East Longitude. Wind speed datasets and other information can be obtained at the office as needed.

3.5 Data cleaning and feature selection

Supervisory Control and Data Acquisition (SCADA) is a dataset obtained to produce missing data due to the equipment used or errors in measuring the actual data. The application of LSSVM parameters and the same or different particle sizes will affect the performance of the wind speed prediction model. However, the missing data can be replaced with a training machine. Modeling wind speed prediction against time series can be obtained from a training machine, where the time series is treated as univariate for every change of 20 min or more [46, 47]. The SVMD model is used to obtain the initial wind speed as intrinsic data, then normalized and produces its optimal value.

3.6 Modeling of the proposed method

This study proposes an SVMD-EBQSPO-LSSVM-LSTM method for short-term wind speed forecasting. Each modal component generated by SVMD is modeled by the LSSVM algorithm optimized by EBQSO for the error sequence, and then the LSTM method is used. To implement QPSO with Elitist Breeding (EB-QPSO) to find the optimum values of LSSVM hyperparameters and window sizes, the parameters must first be encoded as chromosomes. The regularization parameter, kernel parameter, and window size must contain three position values, which represent each chromosome as a particle with three genes and limit the number of transposons and the size of each transposon to one. Furthermore, choosing a good fitness function is a key component of the successful implementation of evolutionary algorithms. In this paper, the inverse of the Mean Squared Error (MSE), is chosen as the fitness function of the EB-QPSO algorithm. This is mainly due to the simplicity of calculating MSE compared to other metrics such as Root Mean Squared (RMS).

3.7 Evaluation for RMSE

Therefore, the SVMD-EBQPSO-LSSVM-LSTM model first optimizes the LSSVM parameters and window size using each mode as the training and validation sets by maximizing the fitness function (*i.e.*, the inverse of the MSE). Then the LSTM network models a sequence of errors that replace the difference between decomposed mode aggregates and original wind series. The final prediction result is calculated by summing the intrinsic mode prediction values and error values.

One of the challenges in aggregate sampling is the size of the window used. For each decomposed value the order of the errors can be different, resulting in a length mismatch. The solution to this problem is to first calculate the difference between the maximum window size and the chosen window size for a given series. Assuming that the difference is denoted as DI, the first DI value of the series is divided, resulting in a length mismatch for all series to be added.

4 Results and discussion

4.1 Performance evaluation of the EBQPSO algorithm using benchmark functions

To compare the performance of the EBQPSO optimization algorithm with PSO and QPSO, four well-known benchmark functions are considered. These functions are Sphere (F1), Ackley (F2), Griewank (F3), and Mc Cormick (F4), and mathematical expressions.

Each experiment was performed five times to produce statistically convincing results about its performance. The number of iterations taken was 100, and the population size was 25. The D dimension of the functions F1, F2, and F3 was set to 20, while F4 was 2. For the final results of each algorithm, the mean and standard deviation were compared with the global minimum of the benchmark function. It can be observed from the table, EBQPSO produces the minimum closest to the global minimum of the functions F1, F2, and F4, while producing the same minimum as QPSO for F4. We believe that this performance difference can be improved if more trials are used.

4.2 Experimental setup

Parameter settings for the EBQPSO algorithm when implemented to optimize the LSSVM parameters and window size for each time modal component. The maximum number of generations is set to 100 and the population size is set to 25. Since we are optimizing three hyperparameters, the problem dimension is set to 3, the skip percentage is set to 1, and the number of transposons is also set to 1. The skip rate is chosen to be 0.3, which indicates the transposon operator is activated with a probability of 0.30, otherwise, the algorithm continues with regular QPSO. The value is set to 5 to start elitist breeding every 5 generations. Choosing the right search space is also important, setting the minimum value of both to 0.0001 and the maximum to 10000. The minimum value of the window size is 1 and the maximum is 25. In addition, we map the search space to perform a logarithmic scale to increase the search power and help convergence to the optimal value with fewer iterations. This EBQPSO configuration is used to optimize the LSSVM model when trained on all the modes of the disentangled dataset. The error sequence is modeled using an LSTM network with parameter settings selected through trial and error. The error to produce the best architecture, after calculating the error sequence using inequality LSTM was trained and tested using the wind speed dataset.

The proposed approach is also compared with other competitive methods. The competitive methods considered in this study are LSSVM, SVMD-LSSVM, CNN, LSTM, CNN-LSTM, SVMD-CNN, SVMD-LSTM, and SVMD-CNN-LSTM. CNN, LSTM, and CNN-LSTM and their hybrid varieties have been widely used in the literature for wind forecasting. The proposed SVMD method is also an important approach to determine whether the proposed method is superior to other reference models. Parameter settings of the prediction methods and comparison of these methods submitted with EBQPSO-LSSVM it can be concluded whether the addition of the SVMD algorithm will provide performance improvements.

4.3 Wind speed model

The relationship between the intrinsic mode function and the original wind series can be evaluated using the correlation value. The correlation value can help us understand whether the SVMD algorithm decomposes the wind speed into independent modes and whether the center frequency of each decomposed signal is adequately separated. The diagonal correlation matrix of IMF for April and May datasets. It is observed in the figure that the highest correlation values are 0.29 and 0.16 and occur between IMF-1 and IMF-2 for the datasets respectively. The other correlation values are very small, while the output of these small correlations is that the SVMD algorithm produces independent and distinct IMFs. It also shows that the IMF center frequencies are further apart from each other.

4.4 Performance of the proposed method

In this study, seven competitive models are considered to measure the performance of the proposed models. The methods used are LSSVM-EBQPSO, CNN, SVMD-CNN, LSTM, SVMD-LSTM, CNN-LSTM, and SVMD-CNN-LSTM.

Performance overview of all methods using various metrics for a dataset. The SVMD-EBQPSO-LSSVM-LSTM method outperforms all other methods because all performance metrics are both datasets.

The dataset on the proposed model obtained Root Mean Squared Error (RMSE) of 0.703, Mean Absolute Error (MAE) of 0.512, Mean Absolute Percentage Error (MAPE) of 5.9%, R^2 of 0.796, and correlation coefficient of 0.892. The model with the lowest performance was the SVMD-CNN-LSTM model, while the model with the second highest performance was the SVMD-CNN model. There was a performance improvement of 2.42% with the proposed method compared to the second-best model in terms of RMSE, 4.10% in terms of MAE, 3.38% in terms of MAPE, and 1.27% in terms of R^2. In addition, a performance difference of 33.85% was obtained between the proposed method and the lowest performing method in terms of RMSE, 48.82% in terms of MAE, 40.68% in terms of MAPE, 25.35% in terms of R^2, and 1.25% in terms of correlation coefficient.

The performance margin of the proposed method is more prominent, especially in terms of RMSE and MAE showing that the SVMD-EBQPSO-LSSM-LSTM model is superior in capturing large errors and is less sensitive to outliers.

Similarly, for the May dataset, the proposed model produces results that are superior to the benchmark methods, except for the SVMD-LSTM model, where both methods obtain similar results. The proposed method obtains an RMSE score of 0.856, MAE of 0.661, MAPE of 13.0%, R^2 of 0.817, and a correlation coefficient of 0.905. The method with the lowest performance is the EBQPSO-LSSVM model. The proposed system achieves 31.66% RMSE, 32.68% MAE, 28.46% MAPE, 19.62% R^2, and a correlation coefficient increase of 9.17% compared to the EBQPSO-LSSVM model. These performance improvements prove the impact of the SVMD and LSTM methods on the overall model improvement.

Compared with the SVMD-LSTM model, the proposed model obtains less than 1% higher MAPE score with the same performance in terms of RMSE and R^2. Furthermore, the SVMD-LSTM method yields a performance improvement of less than 1% in MAE and a correlation coefficient improvement of less than 0.2%, which according to all reports is almost negligible. Thus, although the performance of the SVMD-LSTM model is close to that of the proposed method for the May dataset, this similarity disappears, and the superiority of the proposed method is maintained when both datasets are considered. On average, the proposed model achieves 5.76% RMSE, 8.85% MAE, and 5.93% MAPE improvements over SVMD-LSTM.

To further explain the forecasting ability of the proposed method, show actual value versus predicted value for the function proposed and benchmark functions, along with error indices for both datasets. The error values are calculated by taking the difference between the actual wind speed and the speed predicted wind. The adaptability of the proposed approach is quite good, as it can recognize all test set patterns with high accuracy. Furthermore, the benchmark method also shows great generalization ability on the test set. Conclusively validating that the proposed system shows better generalization ability by simply observing the graphs is a difficult task. This is because the size of the wind test set is not large enough to identify the nuances that explain the superiority of the proposed model. However, it can be observed that the error index is slightly smaller in magnitude than the benchmark model.

Another important performance assessment tool for forecasting models is a linear fit. An ideal model produces the same predicted value for each actual value. In such a case, the slope of the linear plot is one. In general, a good fit keeps the predicted values close to the actual values. Therefore, the robustness of the model is inferred from how dense the dots are and the slope of the linear plot.

For the April dataset, we have the proposed SVMD-EBQPSO-LSSVM-LSTM model points denser around the linear plot. In addition, the slope of the linear plot of the proposed approach, 0.7889, is the closest to one. From this data, it can be concluded that the proposed approach shows better forecasting ability than the benchmark method. Thus, the dataset for the proposed method reaches the densest point in the linear fit and achieves the highest slope, 0.7812, when compared to the benchmark method. Therefore, it can be concluded that the proposed method is the best for the test set fit.

For each dataset, it can be observed that for all models, the distribution can be approximated by a normal distribution with varying mean and variance. In general, a good fit is expected to have a narrow range and be centered in the middle of the distribution. The proposed method produces error distribution with mean lowest and variance. The SVMD-CNN model also has the same variance but its average is higher than the proposed method.

Similarly, the proposed method produces a residual error distribution with the mean value closest to zero and the lowest variance compared to the benchmark model. The CNN model is another model that achieves the same mean value, but its variance is larger than the proposed approach. Therefore, the proposed model is further strengthened in its superiority in accurately predicting and generalizing unseen sequences, as it shows superior performance compared to well-known models validated using various forecasting metrics and separate datasets.

4.5 Statement of significance

Based on the exploration and utilization of wind energy, it has now been used as a renewable energy source. Integration of wind energy with other energy sources is an alternative system to strengthen future energy. Prediction of wind speed becomes a hybrid-based renewable energy as an option. Successive combination model Variational Mode Decomposition (SVMD) is based on the LSSVM model to obtain parts of the system with new variants. In addition, a hybrid model for short-term WSF that takes into account the suitability of the LSSVM model for average data size and computing resources with the improved QPSO algorithm to optimize its parameters, with the LSTM network by modeling irregular sequences, and the advantages of the SVMD decomposition algorithm. For the wind speed prediction of the above system, the RMSE, MAE, MAPE, and R^2 models are used as validation of the tested system, and significant results are obtained.

5 Conclusion

Current technological developments have provided a new finding for the utilization of renewable energy as a future energy source that is environmentally friendly without the resulting emissions. The development of AI combined with machine learning contributes to hybrid machine learning applied to renewable energy. The model proposed in this study can predict the potential for non-continuous and non-fixed wind speeds to provide a source of future energy generation. Taking two sets of wind speed data obtained from a set of local wind speeds has provided the best contribution performance to other forecasts. In addition, the proposed model has contributed to predict wind speed and has been validated using RMSE, MAE, MAPE, and R^2 models with the results The dataset on the proposed model obtained an RMSE of 0.703, MAE of 0.512, MAPE of 5.9%, R^2 of 0.796, and a correlation coefficient of 0.892.

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Conflicts of interest

The authors declare that they have no conflicts of interest.

Data availability statement

No data were used to support this study.

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