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Research Article

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Hybrid Energy Integration for Wind Speed Prediction

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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 in strengthening current energy. However, this paper only discusses the prediction of wind speed into renewable energy by integrating based on hybrid. Combination of systems with the Successive model Variational Mode Decomposition uses the Least Squares Support Vector Machines model to obtain parts of the system with new variants. For the wind speed prediction of the system above, the RMSE and MAE models are used as validation of the tested system and the results show that the RMSE model is at a value of 1.2-32.7%, while the model with MAE is worth 2.06-40.7%.

Keywords: Wind Speed Prediction, Renewable Energy, RMSE, MAE

1. Introduction

The development and advancement of technology at this time, then the change in the use of fossil energy is decreasing, because it impacts air and environmental pollution [1-3]. As a substitute for the lack of energy, the transition to renewable energy is a form of public concern to maintain green energy [4-6]. Wind speed in tropical areas has good potential to be used as a source of green energy, especially to turn wind turbines, because they have high efficiency without the pollution produced [7,8]. The change in kinetic energy created by wind turbines into electrical energy is easy to operate and cheap [9,10].

Wind power utilization has several obstacles because wind speed always fluctuates, which affects the wind produced when turning the turbine [11]. This wind power cannot be stored for future use, but wind energy can be stored in batteries that can be used as a source of electricity at a certain time [12]. Managers always think about how to balance between producers and users to have certainty in the use of this wind energy continuously [13,14].

Wind power prediction serves the demand for electrical energy as a consideration model for minimal operational costs, but has optimal benefits [15]. An obstacle that is always experienced when integrating into a network system where fluctuating wind speeds and fairly high operating costs will result in uncertainty and are difficult to predict and possible damage can occur [16]. Therefore, integration for predicting wind velocity accurately and reliably becomes important to minimize operational costs.

The wind speed prediction strategy consists of an initial forecast to determine the potential as a source of wind turbine driving which is used as a benchmark to determine the capacity of the turbine to be installed [17,18]. The next strategy is a direct forecast of the existing conditions of wind speed at the research location. These two strategies are the best choices that can be accepted theoretically and practically for predicting the potential of wind speed as a renewable 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 minutes to 6 hours, 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, the development of power plants is concentrated on low-emission green energy, such as wind energy. Therefore, this study focuses on the prediction of hybrid power plants based on integrated technological developments, namely short-term wind speed predictions by combining advances in AI technology. Combination of systems with the Successive model Variational Mode Decomposition uses the Least Squares Support Vector Machines 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. Next, the error sequence trend obtained from the mode proposed and the wind data is modeled by 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.

1.1 Literature Review

For prediction models, Accurate wind speed and wind power are needed. In the academic and industrial worlds, related research has been carried out on wind speed [23]. Wind speed prediction has been carried out using physical methods, statistical methods, AI-based methods, and hybrid methods. For the physics method based on numerical weather prediction (NWP) and the utilization of weather variables [24]. Using the proposed sequence transfer correction algorithm (STCA) for NWP wind speed sequences which is a new forecasting method.

The statistical model is an ARMA model that utilizes a method using wind speed and direction forecasting by separating wind speed into lateral and longitudinal space, forecasting each individually, and combining them to obtain the final forecast [25]. Another model used is ARMAX to produce superior performance compared to other models. A weakness of Statistical models have a simple structure, fast computing time, and strong interpretation capabilities, but they take longer to run, so forecast accuracy decreases. As a result, statistical methods will fail if they are related to nonlinear relationships in time series. Statistical methods have good suitability for geostationary time series rather than non-stationary series, and real wind data are mostly non-stationary [26,27].

AI-based algorithm models utilize machine learning and deep learning algorithms, so they have the best accuracy and strong ability to handle nonlinear and nonstationary data for wind forecasting applications, such as those used in ANN models ELM models, and others [28]. For self-learning and non-linear mapping, ANN models are used for 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 an improvement of SVM that handles linear equations, but this method has been widely used in WSF, LSSVM relies on two important hyperparameters that greatly affect the overall prediction performance [29]. These two hyperparameters, known as the regularization parameter and the kernel parameter, must be chosen carefully to avoid overfitting or underfitting [30]. A new proposal for PSO algorithm to obtain optimal parameters of LSSVM trained using data set collected from wind farms in Indonesia. WSF methods short-term using the improved PSO method on a combination of persistence methods, radial basis functions (RBF), 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 long-term term models (LSTM) [31,32]. 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 issue related to the relationship between turbulence intensity and performance at different time intervals is not addressed. Although results were obtained, the research results showed that the accuracy can be further improved by increasing the number of feature maps and the number of neurons using more hardware resources. The LSTM model was implemented to analyze Primary data analysis (PDA) and was first used to reduce the dimensionality of meteorological data and differential evolution (DE) algorithm was applied to generate optimized values of LSTM hyperparameters such as learning rate, number of hidden layer nodes, and batch size [33]. Overall, the advantages of deep learning models become more apparent when there is a large amount of data supply 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 mode phenomenon that occurs in EMD and the high prevalence of noise in EEMD residuals, the accuracy improvement is limited. Therefore, SVMD is a better alternative for parsing time series data such as wind speed [34].

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 QPSO algorithm to optimize its parameters, with an LSTM network to model irregular sequences, and the advantages of the SVMD decomposition algorithm. Compared to other techniques. This work is novel because it is the first to attempt to use an improved QPSO algorithm based on the transposon operator principle to optimize LSSVM parameters.

2. Methodology

2.1 SVMD Model

The VMD model is a mathematical model that utilizes time series signals and K sub-signals non-recursively [35]. The time series used does not depend on the sample rate and interference. Taking K sub-signals when the decomposition process begins to produce a low K as a duplicate mode and a high K will be at the mixed mode value so that the selection of an inappropriate K will result in a decrease in the performance of the algorithm and this results in a decrease in the wind speed prediction results. The VMD model that has been presented is of concern to reduce the performance degradation of wind speed, so a model is needed to overcome this with sequential variational mode decomposition (SVMD), where in this model the K value will be extracted before being used to produce the expected mode spectrum [36,37].

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 modes and the original signal to be processed [38,39]. The original decomposition signal that has been extracted gives a value that is around the center frequency which is the main criterion in the VMD model, while the minimal spectral overlap and other residual signals are minimized for the reconstruction of existing modes and other residual signals [40]. The SVMD model algorithm is shown in Figure 1.

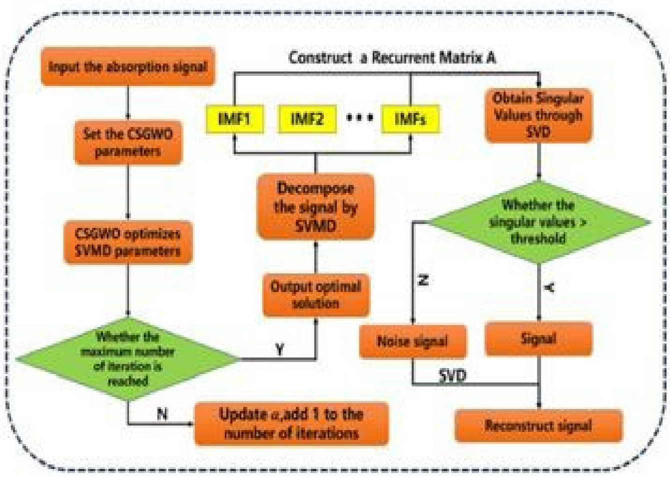

Figure 1: Flowchart of the SVMD Model

2.2 LSSVM Model

The LSSVM model provides an improved SVM model by utilizing the least squares for efficient patterns of classification and regression inputs used to produce linear optimization of the original signal. SVM has the advantage of learning from sophisticated patterns in the data set delivered by the Kernel function [41]. However, learning large data is not able to execute it. The LSSVM model can execute large data by converting inequality into controlled equality for complex linear optimization and expected function convergence [42]. The original wind speed and SVMD model are shown in Figure 2.

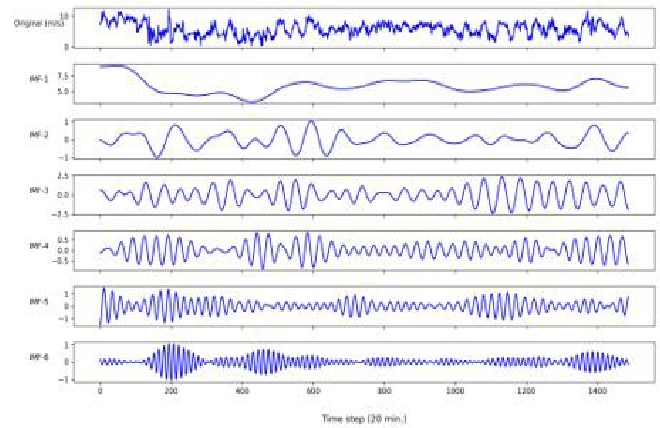

Figure 2: Original Wind Speed and SVMD Mode

The LSSVM model maintains the trade-off that a large error penalty will result in the model fitting the data pattern and data noise to produce the worst generalization model ability. For small values, the model will be under-fit, meaning it fails to learn patterns from the given training set.

2.3 QPSO Model

Model QPSO works on new particle group optimization (PSO) by simulating the quantum mechanics of particles. This model will affect the position of the surrounding delta model particles by utilizing the best position to improve the global search. The movement of QPSO particles in quantum space without spin by utilizing the estimated probability density function to determine its optimal point [43]. The first PSO for particle initialization repeatedly 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 hurt all large particles. Development of the QPSO model to find optimal parameters on LSSVM by building a group of data for breeding and application to obtain various particles on long-term memory (LSTM) swarms developed from RNN models to overcome vanishing gradients. For LSTM units consist of cells, input gates, output gates, and forget gates. 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 passed and sets a value of zero or one.

2.4 Data set

The LSTM model is a deviation model between the original mode number and the original wind speed [44]. This model can handle vanishing and exploding gradients, so the LSTM model is more suitable for the non-linear and non-stationary performance of errors.

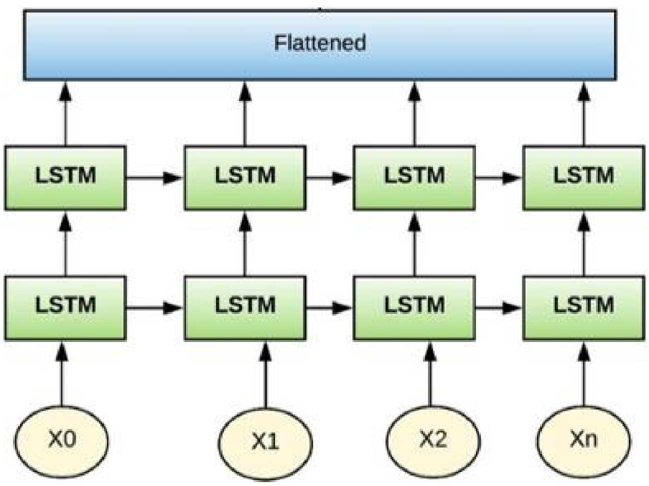

Figure 3: LSTM used for Modeling

Dataset collection in this study was obtained from data from the Meteorology, Climatology and Geophysics Agency (MCGA) of Medan city which is located at 3°27'–3°47' North Latitude and 98°35'–98°44' East Longitude. Datasets for wind speed and other information can be obtained at the office according to their needs.

2.5 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. Predictive modeling of wind speed against time series can be obtained from the training machine, where the time series is treated as univariate for every change of 20 minutes or more [45,46]. The SVMD model is used to obtain the initial wind speed as intrinsic data, then normalized and to produce its optimal value.

2.6 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 an EBQSO-optimized LSSVM algorithm. For the error sequence, the LSTM method is used. To implement QPSO with elitist breeding (EB-QPSO) for searching the optimum values of LSSVM hyperparameters and window sizes, the parameters should first be encoded as chromosomes. The regularization parameter, kernel parameter, and window size should contain three positional values, which denote each chromosome as a particle with three genes and limit the number of transposons and the size of each transposon to one. Furthermore, selecting a good fitness function is a key component of the successful application of evolutionary algorithms. In this paper, the inverse of the mean square error (MSE), is chosen as the fitness function of the EB-QPSO algorithm. This is mainly due to the simplicity of computing MSE compared to other metrics such as root mean squared (RMS).

2.7 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 mean squared error). Then the LSTM network models a sequence of errors that replace the difference between the decomposed mode aggregates and the original wind series. The final prediction result is calculated by summing the intrinsic mode prediction values and error values.

One of the challenges when taking aggregates is that the window size used for each decomposed value and 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 values of the series are divided, resulting in a length mismatch for all series to be added.

3. Results and Discussion

3.1 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 dimension D of the functions F1:F2 and F3 was set to 20, while F4 was 2. For to summarize the final results of each algorithm in terms of mean and standard deviation are compared with the global minimum value of the benchmark function. As can be observed from the table, EBQPSO produces the minimum values closest to the global minimum values of the functions F1, F2, and F4, while producing the same minimum value as QPSO for F4. We believe this performance difference can be improved if more trials are used.

3.2 Experimental Setup

Parameter settings for the EBQPSO algorithm when implemented to optimize the LSSVM parameters and window size for each time modal component. We set the maximum number of generations to 100 and the population size to 25. Since we are optimizing three hyperparameters, the problem dimension is set to 3, the skip percentage 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: we set 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 improve 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 disentangled modes of the dataset. The error sequence is modeled using an LSTM network with parameter settings chosen through trial and error. Errors to produce the best architecture. After calculating the error series using equality, LSTM is 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. By combining these methods, the proposed SVMD method is also an important approach to determine whether the proposed method is superior to these benchmark models. Parameter settings of the prediction methods and comparing the methods proposed with EBQPSO-LSSVM, it can be concluded whether the inclusion of the SVMD algorithm will provide performance improvements.

3.3 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. We can observe from 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 in magnitude. These small correlation outputs show that the SVMD algorithm produces independent and dissimilar IMFs. It also shows that the center frequencies of the IMFs are farther apart from each other.

3.4 Performance of the Proposed Method

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

Illustrate the performance of all methods using various metrics for the datasets. As can be seen in the table, the SVMD- EBQPSO-LSSVM-LSTM method outperforms all methods in terms of all performance metrics for both datasets.

The dataset on the proposed model obtained an RMSE of 0.703, MAE of 0.512, MAPE of 5.9%, R2 of 0.796, and correlation coefficient of 0.892. The model with the lowest performance is the SVMD-CNN-LSTM model, while the model with the second highest performance is the SVMD-CNN model. There is 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 R2. In addition, a performance difference of 33.85% is obtained between the proposed method and the method with the lowest performance in terms of RMSE, 48.82% in terms of MAE, 40.68% in terms of MAPE, 25.35% in terms of R2, and 1.25% in terms of the correlation coefficient.

The performance margin of the proposed method is more prominent, especially in terms of RMSE and MAE, which show 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 RMSE scores of 0.856, MAE of 0.661, MAPE of 13.0%, R2 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% R2, 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 R2. Furthermore, the SVMD-LSTM method yields less than 1% performance improvement in MAE and less than 0.2% improvement in correlation coefficient, which according to all reports are almost negligible. Thus, although the performance of the SVMD-LSTM model is close to 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 improvement 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 predicted wind series. The adaptability of the proposed approach is quite good, as it can recognize all the test set patterns with high accuracy. In addition, 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 indices are 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 points are and the slope of the linear plot.

For the April dataset, we have the proposed SVMD-EBQPSO-LSSVM-LSTM model points that are 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, it can be concluded that the proposed approach shows better forecasting ability than the benchmark method. Thus, the dataset for the proposed method achieves the densest points on 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 closest to zero and the lowest variance compared to the benchmark model. The CNN model is another model that achieves the same mean but its variance is larger than the proposed approach. Hence further strengthens the superiority of the proposed model in accurately predicting and generalizing unseen sequences, as it shows superior performance compared to the well-known models as validated using various forecasting metrics and separate datasets.

4. 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 artificial intelligence (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.

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