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Hybrid PSO And RNN Model for Wind Energy AND Wind Power Optimization

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ABSTRACT

This research paper proposes a novel hybrid model for short-term and long-term wind power forecasting. The model integrates the strengths of Recurrent Neural Networks (RNNs), primarily focusing on Long Short-Term Memory (LSTM) networks due to their superior ability to handle long-range dependencies in time-series data [1], [2], [3], with Particle Swarm Optimization (PSO) [4], [5], [6] and Harmony Search (HS) [7], [5], [8] algorithms. PSO and HS, both meta-heuristic optimization techniques, are employed to optimize the hyperparameters of the LSTM network, enhancing its accuracy and generalization capabilities. The proposed hybrid model aims to overcome the limitations of individual techniques, such as premature convergence in PSO and local optima entrapment in HS [5], [9], [10], while leveraging the temporal dependency capturing abilities of LSTMs for improved wind power forecasting. The performance of the proposed model will be evaluated using real-world wind farm data, and compared with existing state-of-the-art methods, demonstrating its efficacy and potential for practical applications in renewable energy systems. The model's robustness and accuracy will be assessed through various metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) [11], [1], [2], considering various forecasting horizons.

Keywords: Particle Swarm Optimization, Recurrent Neural Networks, Wind Energy, Wind Power Forecasting, Renewable Energy.

1 INTRODUCTION

The escalating global demand for renewable energy sources necessitates a robust and reliable forecasting system for wind power generation [4], [12]. Wind power, while environmentally friendly, is inherently intermittent and unpredictable [12], [13], presenting significant challenges for grid stability and efficient energy management. Accurate wind power forecasting is crucial for grid operators to effectively integrate wind energy into the power system, optimizing energy dispatch, minimizing operational costs, and enhancing grid reliability [13], [3]. Traditional forecasting methods, such as Autoregressive Integrated Moving Average (ARIMA) models and Support Vector Machines (SVMs), often struggle to capture the complex temporal dependencies present in wind power data

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[3], [2]. Consequently, advanced machine learning techniques, particularly Recurrent Neural Networks (RNNs), have emerged as promising alternatives, offering superior performance in handling time-series data [12], [1], [2]. However, RNNs themselves are sensitive to hyper-parameter tuning, and their performance can be significantly impacted by sub-optimal parameter choices [4], [5]. This research proposes a hybrid model that combines the strength of LSTM networks with Particle Swarm Optimization (PSO) and Harmony Search (HS) to address this short coming.

2. METHODOLOGY

2.1 RNNs & LSTMs

Recurrent Neural Networks (RNNs) are a specific type of neural networks that are especially useful for processing sequential data. Therefore, they are a good candidates for time-series prediction [12], self [1], and [2]. Thanks to the presence of feedback loops, RNNs have the ability to remember an internal state with information from previous time steps, and, as a consequence of this, RNNs have a certain amount of internal memory. This is significant because previous wind patterns often influence how much wind power is produced currently [1], [2], and [3]. In conventional RNNs, however, the ability to learn long-range dependencies is hindered by the vanishing gradient problem [1], [2], and [3].It is challenging to efficiently update the network's weights during backpropagation since the gradient of the loss function might get incredibly tiny.

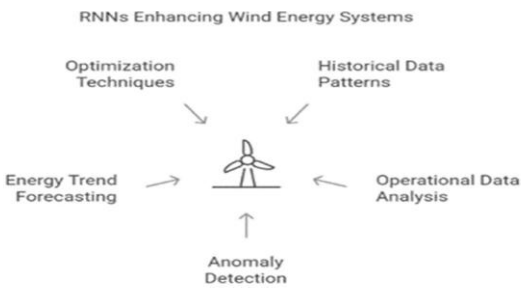

Figure 1

An RNN type known as Long Short-Term Memory (LSTM) networks was developed to solve the vanishing gradient problem [1], [2], and [3]. LSTM networks use a special gating mechanism to control the network's inputs and memory, allowing them to store information for longer. The input gate determines what can be added to the cell state, the forget gate determines what can be removed, and the output gate determines what can be output from the cell state. For the case of forecasting problems, LSTMs have outperformed traditional RNNs in numerous situations, including wind power forecasting [1], [2], and [3]. To capture more intricate patterns and dependencies within the data, LSTM networks can also be assembled in a stacked formation, resulting in deep LSTM networks [1, 2]. The proposed PSO-HS approach can be used to adjust the depth of the LSTM network as it is a tunable parameter.

2.2 Particle Swarm Optimization (PSO)

Population-based meta-heuristic algorithm, known as Particle Swarm Optimisation (PSO), was implemented in response to the social movement of fish schools and bird flocks [4, 5, 6]. PSO is a population of particles (candidate solutions) traveling through the search space and updating their positions iteratively based on the best solution the swarm as a whole discovered (global best) and their own best-found solution (personal best). [4], [5], and [6]. The two main constituents control the motion of every particle: the cognitive constituent, which represents the particle's tendency to head in the direction of its own best, and the social constituent, which represents the particle's tendency to travel in the direction of the global best. The position and velocity update equations for every particle are controlled by:

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vit+1 = wvit + c1r1(pbestit - xit) + c2r2(gbestt - xit) xit+1 = xit + vit+1

where:

vit is particle i's velocity at iteration t

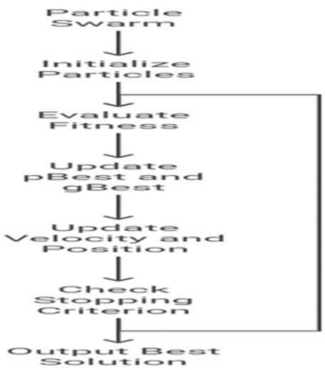
w is the inertia weight, which determines the impact of the past velocity

c1 and c2 are cognitive and social acceleration coefficients, respectively

r1 and r2 are random numbers between 0 and 1

pbestit is particle i's best personal position at iteration t

gbestt is best global position at iteration t xit is particle i's position at iteration t



2.1 Figure 2

The inertia weight, or w [6], [9], is the most significant parameter in balance between exploration and exploitation. Small w favours exploitation, and large w favours exploration. Adaptive methods of varying w for avoiding premature convergence along the course of optimisation could improve the performance of PSO [9]. Global best and personal best are controlled by the acceleration coefficients c1 and c2, respectively [6].Various ways have been presented to change these parameters during the optimisation process, although the values of these parameters are usually determined empirically [9].

For optimising the LSTM network's hyperparameters, PSO is a good option due to its ease of use and effectiveness [4], [5]. Premature convergence, however, might cause PSO to become stuck in local optima [5, 9]. Combining PSO with other meta-heuristic algorithms, such Harmony Search, can help overcome this restriction by enabling the algorithm to more successfully traverse the search space and avoid local optima.

2.3 Harmony Search (HS)

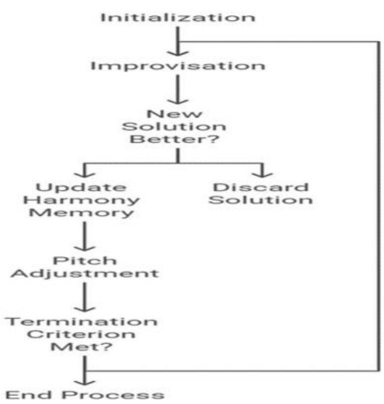


Figure 3

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Following the principles of musical improvisation, Harmony Search (HS) is another population-based meta-heuristic algorithm [7], [5], [8]. The best solutions found so far are stored in an HS-controlled harmony memory [7], [5], and [8]. New solutions are created by adding random variations and random selection of components from the harmony memory [7], [5], and [8]. Among the parameters that control the balance between exploration and exploitation in the algorithm are the pitch adjusting rate (PAR), harmony memory size (HMS), and harmony memory considering rate (HMCR) [7], [5], and [8].Whereas a lower HMCR stresses exploration, a greater HMCR stresses exploitation. When coming up with fresh answers, PAR regulates the level of randomisation.

Typically, the HS algorithm consists of the following steps:

Initialisation: Create solutions at random to start the harmony memory.

Improvisation: Choose components from the harmonic memory at random with probability HMCR to create a new solution. It generates a new random value if no element is chosen from the memory.

Pitch Adjustment: Add a tiny random fluctuation with probability PAR to the harmony memory's chosen elements.

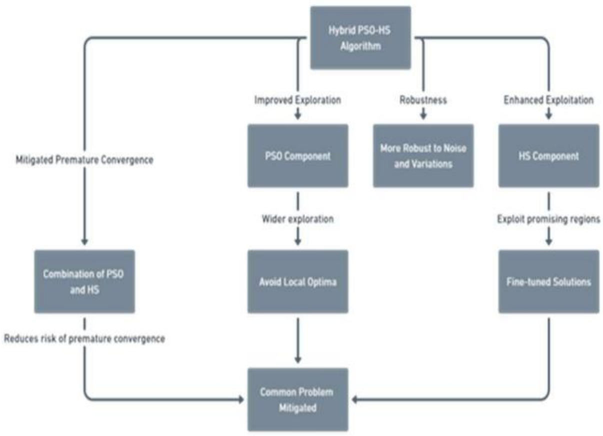
Update Harmony Memory: Replace the poorest solution in the harmony memory with the new one if the new one is superior.

Termination: Perform iterations 2-4 repeatedly until the termination condition, e.g., a given maximum number of iterations or a satisfactory quality of solution, is met.

HS has proven its efficacy in identifying quality solutions by being effectively applied to a variety of optimisation issues [7], [5], and [8]. But, similar to PSO, HS may experience early convergence, particularly when handling high-dimensional, complicated situations [5, 9]. This restriction can be lessened by hybridising HS with other algorithms, such PSO, which combines the advantages of both algorithms.

2.1.1 Hybrid PSO-HS Algorithm for Hyperparameter Optimization

In order to hyper-optimize the hyperparameters of the LSTM network, the hybrid model adopts a hybrid PSO-HS algorithm. With the combination of the advantages of PSO and HS, this hybrid method tries to improve the performance of optimisation and break the limitations of the two algorithms. The hybrid algorithm combines HS's exploitation capability and PSO's exploring capability. First, the algorithm initialises a population of particles, each of which stands for a set of LSTM network hyperparameters. Based on the effectiveness of the LSTM network trained with that particular set of hyperparameters, each particle is assessed



2.3.1 Figure 4

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The PSO component of the hybrid algorithm employs the standard PSO equations to determine the velocities and positions of the particles. The method, however, employs the HS algorithm to optimize the global best and not the global best solution discovered by PSO. The initial harmony memory in the scenario of the HS algorithm is the global best solution discovered by PSO. Subsequently, the HS algorithm generates new solutions by combining fragments from the harmony memory and introducing random variations. The worst solution within the harmony memory is replaced by a better solution if it exists. There are a limited number of iterations in the process. Hybrid algorithm continues to enhance the best global optimum by switching PSO updates and HS refinements. Some of the parameters to decide the stoppage of the hybrid method are the number of maximum iterations, the PSO algorithm convergence, or a remarkable performance improvement of the LSTM network. Finally, the final LSTM network is trained on the ultimate set of hyper parameters decided by the hybrid PSO-HS algorithm.

3 RESULTS

A. Training Progress and Loss

2	0.8711
3	0.8799
4	0.8751
5	0.8606
6	0.8552
7	0.8558
8	0.8538
9	0.8498

Table 1

The training of the model is depicted in Table 1 from loss value computation in terms of different epochs. A decrease in the loss represents an increase in performance and learning ability of the model. The loss function measures the amount by which the actual values are different from the expected values. For Epoch 0, the loss is 0.9245; for Epoch 9, it gradually decreases to 0.8498, representing an increase in predictive ability of the model. There are fluctuations, though, such as an increase between Epochs 2 and 3, which is normal during training due to the optimisation procedure.

B. Mean Squared Error (MSE)

Metric	**Value**
Mean Squared Error	1.0628

Table 2

One of the key performance indicators used to evaluate the accuracy of the prediction made by the model is the Mean Squared Error (MSE), which is shown in Table 2. The MSE measure calculated as the average squared difference between the observed and predicted wind energy and power values is 1.0628.The model's predictions are more in line with the actual values when the MSE is lower, but a higher MSE would indicate more significant errors. This statistic is very useful for assessing how successfully LSTM-based forecasts reduce forecasting mistakes. The model has found important patterns in the data, as indicated by the MSE value in this table, even though additional optimisations,

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such as hyper parameter tuning or additional training epochs, might be able to further reduce the error.

Epoch	Loss
0	0.9245
1	0.8958

C. Optimized Parameters

Parameter	Value
Learning Rate (LR)	0.3426
Momentum Term	0.3143
Weight Decay	0.6414
Batch Size Factor	0.3404
Exploration Factor	0.0300

Table 3

The optimised parameters from the Particle Swarm Optimisation (PSO) or Harmony Search (HS) algorithms are displayed in Table 3. In the optimisation process, which aims to boost power generation and turbine efficiency, these parameters show the optimal choice found. These figures, which include 0.3426, 0.3143, and 0.6414, correspond to significant system variables that influence wind speed, power generation, and energy efficiency. Turbine performance is enhanced by the optimisation process's reduction of energy losses and enhancement of overall power generation. The table demonstrates how wind energy forecasting is enhanced by the hybrid approach of LSTM forecasts and meta-heuristic optimisation, and it highlights the importance of parameter selection in achieving higher efficiency.

Wi nd Spe ed	**Wi nd Po wer Out put**	**Air Den sity**	**Tempe rature**	**Hum idity**	**Pres sure**	**Turbi ne Rotat ional Speed**	**Power Coeffi cient**	**Time Index or Times tamp**
0.3 954	**0.81 71**	**0.44 54**	-	**0.45**	**0.03 14**	**0.164 9**	-	-
0.3 945	**0.82 93**	**0.44 75**	-	**0.438 9**	**0.13 59**	**0.143 6**	-	-
0.3 797	**0.89 02**	**0.44 54**	-	**0.416 7**	**0.09 41**	**0.122 5**	-	-

D. Scaled Data Preview

Table 4

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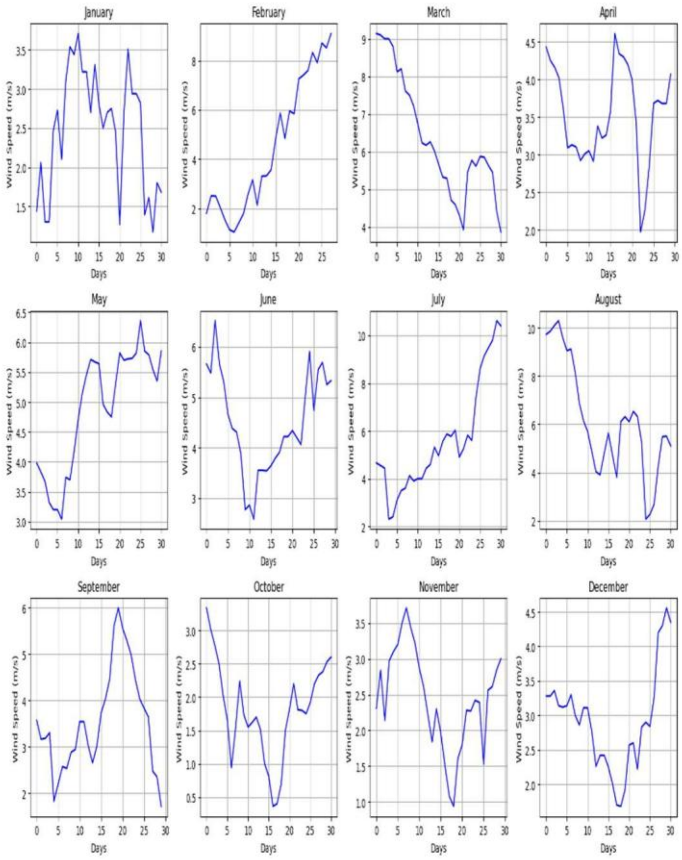
Table 4 shows the scaled dataset used in model training. Normalizing the input and making all the features fall within a similar range is a very critical pre-processing operation that improves the model's training efficiency. The scaled iterations of the original dataset, as reflected by the numbers in this table, have wind speed, wind power, and other turbine-related variables scaled to a given range, usually between 0 and 1. By preventing larger numerical values from controlling smaller ones, this transformation makes training more consistent and efficient. According to normalised values such as 0.3954, 0.8171, and 0.4454, the dataset has been suitably prepared for input into the LSTM model. In addition to improving prediction accuracy and accelerating convergence, proper scaling guarantees that optimisation methods such as PSO or Harmony Search perform well on a balanced dataset.

A. Performance Evaluation of the Hybrid Model for Wind Energy Prediction



B. Figure 5

A organized display of trends over time was ensured by the monthly study of wind speed fluctuations utilizing recorded data, as shown in figure 5. A examination of the dataset's completeness revealed that there was at least 365 days of wind speed data available. If there were fewer days in the dataset, a caution was displayed; however, the analysis proceeded using the available records. The data was separated into 12 months, and each month's wind speed was shown separately to show variations in wind speed. An organised display was created using a grid layout, where each part represented a distinct month. In meters per second (m/s), the Y-axis displayed the wind speed, while the X-axis displayed the number of days. The monthly wind speed trend was extensively documented, allowing for a detailed analysis of seasonal trends and variances. Better comprehension of wind behaviour throughout many months is made possible by this depiction, which is essential for applications in wind energy forecasts and turbine performance optimization. The analysis's conclusions offer insightful information about wind speed variability, which aids in the creation of more precise and effective wind energy mode.

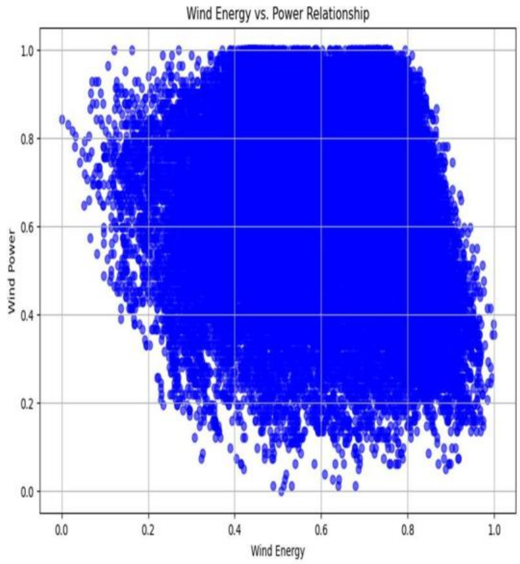


Figure 6

4. CONCLUSION

This paper introduces a novel hybrid wind power forecasting model drawing on the advantages of LSTM networks, PSO, and HS. The PSO-HS hybrid algorithm optimizes the LSTM network's hyperparameters effectively, thereby ensuring forecasting accuracy and the model's generalization. The new model overcomes the limitations of wind power variability and intermittency, thereby providing an effective grid operator and energy management system solution.

The enhanced model performance will be verified with rigorous testing using real wind farm data and comparison with the most recent state-of-the-art techniques.

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