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Wind Speed Prediction Using Chicken Swarm Optimization with Deep Learning Model

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Abstract: High precision and reliable wind speed forecasting have become a challenge for meteorologists. Convective events, namely, strong winds, thunderstorms, and tornadoes, along with large hail, are natural calamities that disturb daily life. For accurate prediction of wind speed and overcoming its uncertainty of change, several prediction approaches have been presented over the last few decades. As wind speed series have higher volatility and nonlinearity, it is urgent to present cutting-edge artificial intelligence (AI) technology. In this aspect, this paper presents an intelligent wind speed prediction using chicken swarm optimization with the hybrid deep learning (IWSP-CSODL) method. The presented IWSP-CSODL model estimates the wind speed using a hybrid deep learning and hyperparameter optimizer. In the presented IWSP-CSODL model, the prediction process is performed via a convolutional neural network (CNN) based long short-term memory with autoencoder (CBLSTMAE) model. To optimally modify the hyperparameters related to the CBLSTMAE model, the chicken swarm optimization (CSO) algorithm is utilized and thereby reduces the mean square error (MSE). The experimental validation of the IWSP-CSODL model is tested using wind series data under three distinct scenarios. The comparative study pointed out the better outcomes of the IWSP-CSODL model over other recent wind speed prediction models.

Keywords: Weather; wind speed; predictive model; chicken swarm optimization; hybrid deep learning

1 Introduction

Weather conditions certainly affect various aspects of life in modern society. Unfavorable weather conditions and events have direct as well as indirect impacts on a large number of businesses and economic fields, like agriculture, transport, and logistics [1]. Precise and prompt weather predictions are significant for various applications facilitating management and planning related to climatic conditions

[2]. Forecasting weather is crucial for predicting natural calamities like hurricanes, extreme rainfall, heat waves, and floods. As wind power has gained significance as a renewable energy over the past few years, wind speed prediction is becoming a prominent tool for productive the effectual and adaptive maintenance of wind parks [3]. However, weather forecasting commonly depends on numerical weather prediction (NWP) techniques for solving complicated arithmetical equations, which pretend thermodynamics and fluids within the natural world's environment as much as possible [4]. This method needs enormous computational power; with current technological tools and equipment, it may take numerous hours to process. Because of its wide computational requisites, the application of NWP methods is practically limited and restricted to more long-run estimations [5]. Therefore, NWP algorithms are utilized for prediction, for example, 3 h ahead. However, as the time to process this forecast takes more than 3 h, the practical usage of this method is limited. These results become a significant gap for short-run weather forecasting, enabling short-term planning [6].

Through technological development and fortifying advocacy for ecological protection, wind energy production is more commercially competitive than coal-fired power production [7]. As wind power can be directly linked to the wind speed, the volatility and instability of wind speed would cause instability in wind energy production, which has a massive effect on the power grid [8]. To minimize the cost of maintenance caused by system failures and performance degradation, precise forecasting of short-term wind speed is greatly needed. To precisely forecast the wind speed and overcome the uncertainty of its changes, several prediction approaches have been devised over the last decades [9]. As per the forecasting duration and application cases, wind speed prediction is classified into two categories, long-term prediction and short-term prediction. In short-term prediction, the wind speed once every 10 or 20 min or an hour is predicted. In the long-term prediction, the forecast can be made after some days or a month [10]. However, the predicting horizon of long-term forecasting becomes comparatively long, and several unknown elements would affect the forecasting outcomes. Thus, short-term prediction is more versatile and realistic in real applications.

This paper presents an Intelligent Wind Speed Prediction using Chicken Swarm Optimization with Hybrid Deep Learning (IWSP-CSODL) model. The presented IWSP-CSODL model estimates the wind speed using a hybrid deep learning and hyperparameter optimizer. In the presented IWSP-CSODL model, the prediction process is performed via CNN-based long short-term memory with autoencoder (CBLSTMAE) model. To optimally modify the hyperparameters related to the CBLSTMAE model, the CSO algorithm is utilized and thereby reduces the mean square error (MSE). The experimental validation of the IWSP-CSODL model is tested using wind series data under three distinct scenarios.

The remainder of the paper is organized as follows, Section 2 analysis the related works involved in Wind Speed Prediction. Section 3 describes the Proposed Wind Speed Prediction Model and estimates the wind speed using a hybrid deep learning and hyperparameter optimizer. Section 4 then analyses the experimental data and results, including a performance comparison with alternative methodologies. Finally, Section 5 concludes the critical results of the proposed research.

2 Related Works

In Trebing and Mehrkanoon [11], a new paradigm based on a convolutional neural network (CNN) is introduced to predict wind speed. Notably, we have shown that, in contrast to the traditional CNN-based models, the presented method can be able to better characterize the spatio-temporal evolution of the wind dataset by learning the basic structure of the input-output relationship from different views (dimensions) of the input dataset. The suggested technique uses the spatiotemporal multivariate multi-dimensional, past weather dataset to learn novel representations intended for wind prediction. With the information attained from the South African Wind Atlas Project, Daniel et al. [12] addressed the prediction of wind speed, an initial input needed for wind energy generation. Prediction can be performed on two days in advance time horizon. Then, we examine the forecasting efficiency of an artificial neural network (ANN) that is trained by using a decision tree, stochastic gradient boosting (SGB), and Bayesian regularization-based generalized additive models (GAMs).

Lin and Zhang [13] established a new hybrid mechanism that might forecast the upcoming wind speed precisely. At first, the original wind speed duration is decomposed through the fast assembling empirical mode decomposition into different subsets that are additionally incorporated by the run test. The space reconstruction occurs by energetically choosing every incorporated subset input and output vector for the forecasting method. In addition, a better whale optimization algorithm was used for optimizing the weight and bias of the extreme learning machine (ELM) model. The authors in [14] predicted the wind speed at a target station in the north of Iran. The grouping of a multi-layer perceptron (MLP) with a whale optimization algorithm (WOA) was utilized for building a novel model with a restricted amount of information (2004–2014). Next, the MLP-WOA method was applied at every ten target stations, with the tenth station for testing and nine stations for training to improve the performance of the succeeding hybrid mechanism. The ability of the hybrid mechanism in wind speed prediction in every target station was contrasted with MLP improved by the genetic algorithm (GA) called MLP-GA and individual MLP without the WOA optimizer.

Geng et al. [15] developed a wind speed forecasting model with robust integration of principal component analysis (PCA) and long short-term memory (LSTM) networks. Initially, PCA is used to decrease the dimension of the original multi-dimension meteorological information that affects wind speed. Furthermore, a differential evolution (DE) technique is developed for optimizing the learning rate, several hidden layer nodes, and batch size of the LSTM network. Liu et al. [16] implement the industry's application of the ML method of support vector regression (SVR) and optimization techniques for control variables that can not only reduce energy use and costs. Also fundamentally improve the efficiency of filter press operation. This will open up some possibilities for the intelligent dewatering process and other forms of industrial production optimization. Zhang et al. [17] designed a combined Wind Speed Prediction Model using a convolutional neural network. The work achieved prediction results that have significant advantages in the spatio-temporal features of Wind farms. The disadvantages of the work is utilized limited parameters to measure the performance.

An enhanced deep learning (DL)-based hybrid model for forecasting wind speed is projected in [18]. The new architecture applies stacked LSTM and system architecture evolution (SAE) networks. The SAE extracts abstract and more profound features from the actual wind speed data. An experimental test was performed to identify an optimum stacked LSTM. The feature extracted from SAE is later transported to the optimum stacked LSTM for the wind speed prediction.

3 The Proposed Wind Speed Prediction Model

In this study, a new IWSP-CSODL model has been developed for effectual and precise wind speed forecasting. The presented IWSP-CSODL model estimates the wind speed using a hybrid deep learning and hyperparameter optimizer.

3.1 Level I: CBLSTMAE-Based Prediction Process

In the presented IWSP-CSODL model, the prediction process is performed by the CBLSTMAE model. The architecture encompasses different frameworks comprising 2 CNN layers and an autoencoder (AE) framework composed of a single LSTM layer as a decoder and a CBLSTM as an encoder [19]. The proposed IWSP-CSODL model used hybrid deep learning technique that combine long short-term memory (LSTM) networks, convolutional neural networks (CNN), and autoencoder (AE) are built and tested on wind datasets for wind speed prediction.

Especially, CNN is skilled in extracting complicated features and might save many different unequal trends [20]. Extracting of complicated features decreases the parameters necessary to make the prediction, hence decreasing the network computation when machinating the performance. The feature extraction of CNN and its down-sampling model decreased the computational time, which makes them better suited for the projected applications [21–24]. In this work, the CNN layer receives eight input constraint parameters influencing the forecasting energy consumption, comprising the week indices (bank, holiday, and weekday weekends) and weather conditions (temperature, dew point, and humidity wind speed). They are additionally processed via the hidden layer to generate an output prepared for the AE framework. The output of the CNN layer was given to the input of CBLSTM, which assists as an input to the AE layer [25–28]. Although CNN extracts significant features from datasets, the CBLSTM-AE layer can be used for sequence prediction and data analysis. To reduce the difficulty of the presented framework, a single LSTM is employed in an AE decoder *vs.* the CBLSTM of the encoder. Furthermore, a single LSTM can learn from temporal dependency from one order to others [29–31]. The encoded data from the output of CBLSTM-AE can be decoded through a single layer of LSTM-AE beforehand, taking place to 2 total connection layers for the final forecasted output. It can be mathematically expressed in the following.

Assume the input vector $x_i^m = \{x_1, x_2, \cdots, x_n\}$, whereby x^m indicates the different input vectors, containing weather data, energy consumption, week index, and so on., of $m \in M$, and n refers to the number of normalized thirty min units for each observation window, which fed as an input vector x_{i^m} into CNN layer, the resultant the output is formulated as follows.

$$y_{ij}^m = \sigma\left(b_j^m + \sum_{m=1}^{M} w_{m,j}^1 x_{i+m-1,j}^0\right) \tag{1}$$

In Eq. (1), y_{ij}^m denotes output vector x_{ij}^m of the preceding layer. b_j^m indicates the bias for *j-th* feature maps, m shows the index value of the filter, w indicates the weight of the kernel, and σ denotes the activation function for CNN. Eq. (2) indicates the output vector for *k-th* convolution layers. In such case, the next convolution layer in the architecture is equated as

$$y_{ij}^{m(k)} = \sigma\left(b_j^{m(k)} + \sum_{m=1}^{M} w_{m,j}^{m(k)} x_{i+m-1,j}^0\right) \tag{2}$$

The pooling layer of the convolution layer samples the activation from mapping features to decrease the parameter count and computational network cost. The *max*-pooling layer characterized in Eq. (3) uses the maximal values from the preceding layer for its downsampling that assists in adjusting the overfitting model.

$$P_{ij}^{m(k)} = \max_{r \epsilon R} y_{i \times T + rj}^{k-1} \tag{3}$$

where y characterizes the pooling size and T denotes stride determining the length of the input dataset.

The output from the maximal pooling layer was given to the input of the BLSTM layer via the gate components. BLSTM comprises dissimilar gates (forget, input, and output gates) in forward and backward directions, and every gate is activated. At the same time, memory cells upgrade the state, characterized as follows in Eqs. (4)–(6) respectively.

$$i_t = \sigma\left(W_{piPi} + W_{hi}h_{t-1} + W_{ci} \cdot c_{t-1} + b_i\right) \tag{4}$$

$$f_t = \sigma\left(W_{p}f^{Pt} + W_{h}fh_{t-1} + W_{c}fc_{t-1} + b_f\right) \tag{5}$$

$$0_t = \sigma(W_{Po}pt + W_{ho}ht - 1 + W_{C0} \cdot c_t + b_0) \tag{6}$$

In the following equation, σ denotes the activation function, b indicates the bias, and c_t shows the cell state. P_t indicates the output of the max pooling layer at t time that encompasses the energy utilization dataset and additional parameters utilized as input to AE through the CBLSTM layer. i_t, f_t, and 0_t indicates the input, forget, and output gates; correspondingly, h_t denotes the hidden state of the BLSTM cell that was upgraded at each t step in backward and forward directions [32–36]. Fig. 1 depicts the infrastructure of the AE technique.

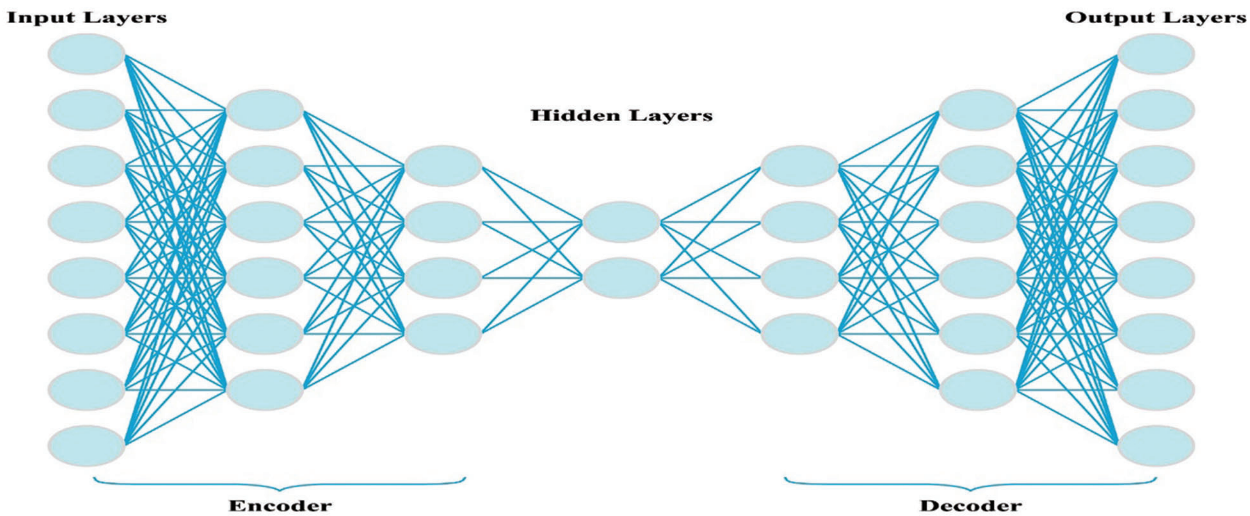

Figure 1: Structure of AE

The cell and hidden states are defined by the gate function of CBLSTM for the hidden and cell states, correspondingly in Eqs. (7) and (8)

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \sigma\left(W_{pc}p_t + W_{hc}h_{t-1} + b_c\right) \tag{7}$$

$$h_t = 0_t \cdot \sigma(c_t) \tag{8}$$

The output of the BLSTM layer was concatenated with backward and forward directions, formulated in Eq. (9).

$$\hat{y} = \sigma\left(\overrightarrow{W_y h_t} + b_y\right) \tag{9}$$

The output of BLSTM $\hat{y}$ was given as an input of the LSTM decoder, whereby the resultant output $\hat{y} = \sigma\left(W_y h_t + b_y\right)$ signifies the input to the two fully connected (FC) dense layers for the last projected output in Eq. (10).

$$d_i^k = \sum_j w_{ji}^k - 1\left(\sigma\left(\hat{y}_i^{k-1}\right) + b_i^{k-1}\right) \tag{10}$$

The CNN layer extracts spatial characteristics from the input dataset, and CBLSTM-AE accepts the feature from a CNN for learning temporal dependency from an estimated output.

3.2 Level II: CSO-Based Hyperparameter Tuning Process

To optimally modify the hyperparameters related to the CBLSTMAE model, the CSO algorithm is utilized and thereby reduces the mean square error (MSE). The CSO approach is preferred over other optimization techniques due to its high parallelism and simplicity [37–40]. The CSO mimics the performance of a chicken swarm and the chicken movement; the CSO is described in the following: CSO contains various groups, and each group has some chicks, hens, and a predominant rooster [41]. The number of chicks, roosters, and hens in the group is established based on the fitness function. The rooster (group head) refers to the chicken that is an optimal fitness value. However, the chick is the chicken that contains the worst fitness value. Most chickens are hens and are arbitrarily chosen to remain in that group. The mother-child and dominance connections in the group stay unchanged and upgraded in the (G) time step. The chicken movement is formulated below is used for rooster updating location given as follows in Eq. (11).

$$X_{ij}^{r+1} = X_{i,j}^{t} * \left(1 + randn\left(0, \ \sigma^2\right)\right) \tag{11}$$

where:

$$\sigma^2 = \begin{cases} 1 & \text{if } \mathrm{f_i} \le \mathrm{f_k} \\ \exp\left(\dfrac{\mathrm{f_k} - \mathrm{f_i}}{|\mathrm{f_i} + \varepsilon|}\right) & \text{Otherwise} \end{cases}$$

where $k \in [1, \ N_r], \ k \neq i$, and N_r denote the rooster count. $X_{i,j}$ denotes the position of rooster count i in j^{th} dimension at t and $t+1$ iteration, $randn\ (O, \ \sigma^2)$ generates arbitrary Gaussian number with mean 0 and variance σ^2; ε indicates the constant with minimal value, and f_i indicates the fitness value of the corresponding rooster i. The formula that employs the hen updating position is shown below in Eq. (12).

$$X_{i,j}^{t+1} = X_{i,j}^{t} + S_1 randn\left(X_{r1,j}^{t} - X_{i,j}^{t}\right) + S_2 randn\left(X_{r2,j}^{t} - X_{i,j}^{t}\right) \tag{12}$$

In which, Eq. (13) calculates the S_1

$$S_1 = \exp\left(\frac{f_i - f_{r1}}{|f_i| + \varepsilon}\right) \tag{13}$$

Then replace the S_1 calculation in Eq. (14).

$$S_1 = \ \exp\ (f_{r2} - f_i) \tag{14}$$

whereas $r1, \ r \in [1, \ldots, N], \ r1 \neq rr$ denotes the index of the rooster, but $r2$ indicates the chicken in the swarm hen or rooster, and a uniformly distributed arbitrary value is produced using *randn*. At last, the formula that applies the chick updating position is given as follows in Eq. (15):

$$X_{i,j}^{t+1} = X_{i,j}^{t} + FL\left(X_{m,j}^{t} - X_{i,j}^{t}\right), \ \ FL \in [0, \ 2] \tag{15}$$

Now $X_{m,j}^{t}$ shows the place of *i-th* chick mother.

Fig. 2 depicts the flowchart of the CSO technique.

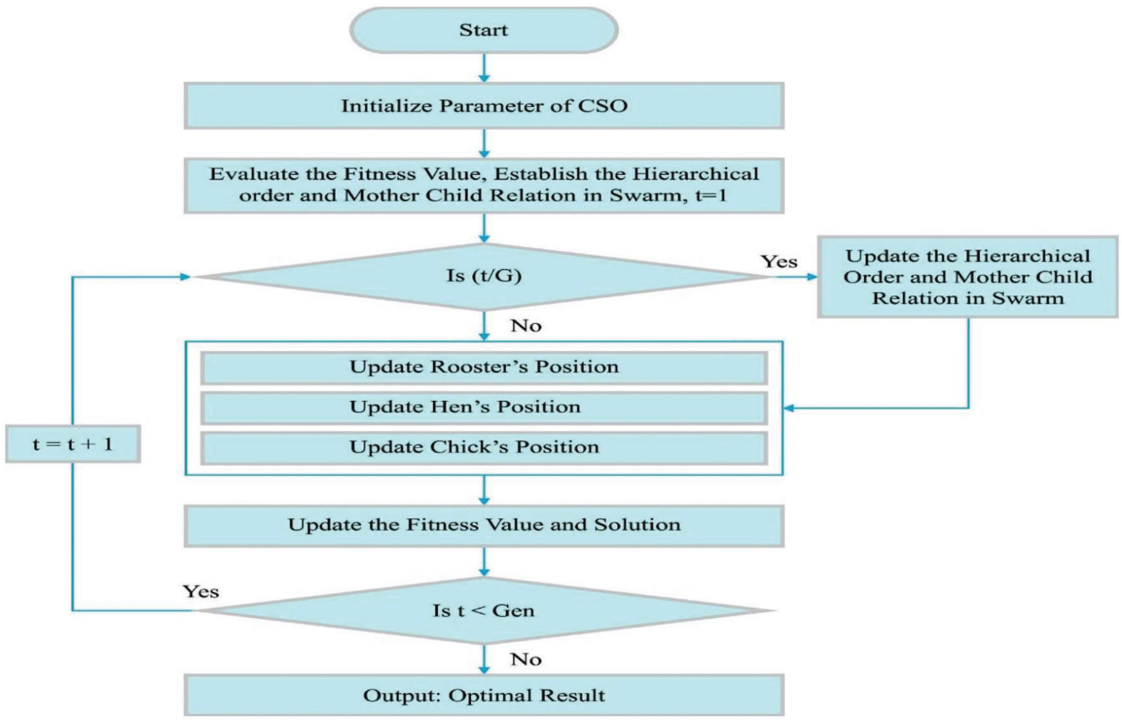

Figure 2: Flowchart of CSO technique

4 Results and Discussion

This section investigates the wind speed prediction outcomes of the IWSP-CSODL model under three distinct scenarios. This proposed work measured the wind speed data of a wind farm, starting from February 1, 2022, to July 30, 2022, with an interval of 3 h, each containing 100 data points in the Kotdwara location. Fig. 3 demonstrates the actual *vs.* predicted wind speed of the IWSP-CSODL model under scenario 1.

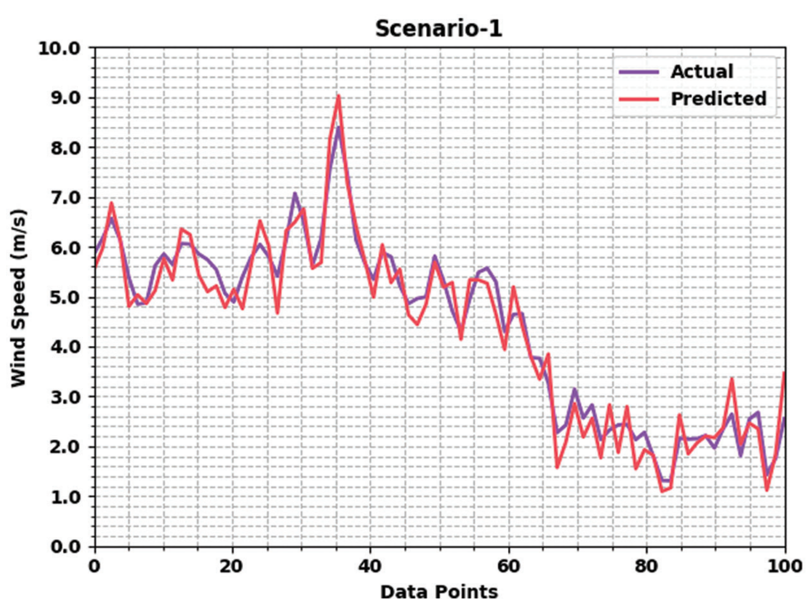

Figure 3: Actual *vs.* predicted analysis of IWSP-CSODL method under scenario 1

The major hardware requirements are a cloud-based supercomputer, server, virtual machine (VM), several sensors, and meet towers for wind speed prediction. The various sensors are wind speed and direction sensors, humidity sensors, radiation sensors, precipitation sensors, modems, and data loggers. It implied that the IWSP-CSODL model has accurately forecasted the wind speed under all data points. The current work uses climate data information that has been downloaded from the website of https://www.indianclimate.com/show-data.php, and the geographical locations of Kotdwara (a City on Uttarakhand state, India country) have been tabulated in this website.

Fig. 4 illustrates the actual *vs.* predicted wind speed of the IWSP-CSODL method under scenario 2. It is implicit that the IWSP-CSODL algorithm has precisely forecasted the wind speed under all data points.

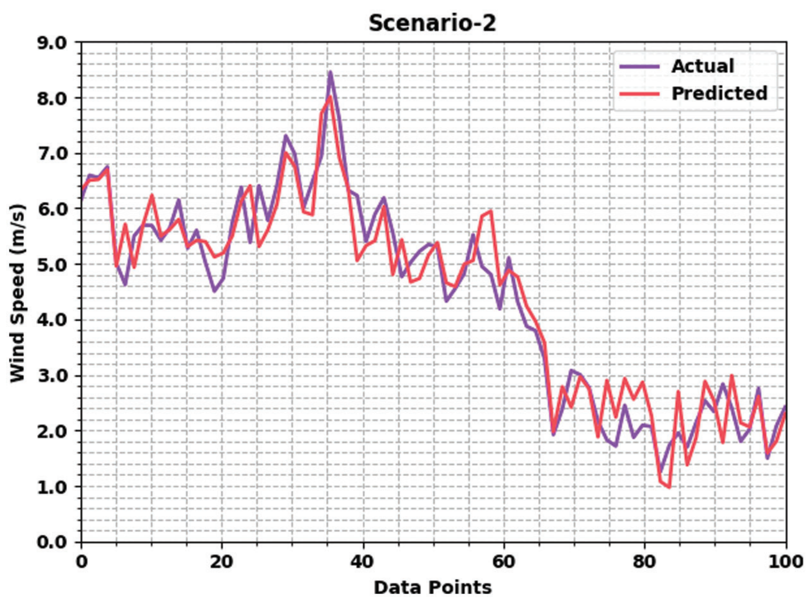

Figure 4: Actual *vs.* predicted analysis of the IWSP-CSODL method under scenario 2

Fig. 5 signifies the actual *vs.* predicted wind speed of the IWSP-CSODL approach under scenario 3. It represented the IWSP-CSODL technique has accurately forecasted the wind speed under all data points.

Table 1 provides an overall wind speed prediction outcome of the IWSP-CSODL model using scenario 1 [42]. Fig. 6 represents a comparison study of the IWSP-CSODL model with other models under scenario 1. The experimental values ensured the effectual predictive outcomes of the IWSP-CSODL model with minimal values of MSE, Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) [43–46]. Concerning MSE, the IWSP-CSODL model has offered a lower MSE of 0.5318. In contrast, the Jaya algorithm based-support vector machines (SVM), absolute shrinkage and selection operator (LASSO), Extreme Gradient Boosting (XGBoost) algorithm, Machine learning and pattern recognition (MLPR), deep belief network (DBN), Gaussian processing regression (GPR), Stacked Sparse Auto-Encoder (SSAE), and governance, risk, and compliance (GrC) models have accomplished increased MSE of 0.6492, 0.6508, 0.6699, 0.6769, 0.7032, 0.7094, 0.7159, and 0.8310 respectively. Moreover Concerning, MAE, the IWSP-CSODL algorithm has presented a lower MAE of 0.4967. In contrast, the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC algorithms have accomplished increased MSE of 0.5899, 0.6089, 0.6203, 0.6215, 0.6236, 0.6385, 0.6505, and 0.6938 correspondingly. At the same time, Concerning MAPE, the IWSP-CSODL technique has offered lower MAPE of 10.1240%, the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC techniques have accomplished increased MSE of 11.6891%, 12.3410%, 12.7580%, 12.8411%, 12.8487%, 13.0254%, 13.5843%, and 14.3853% correspondingly.

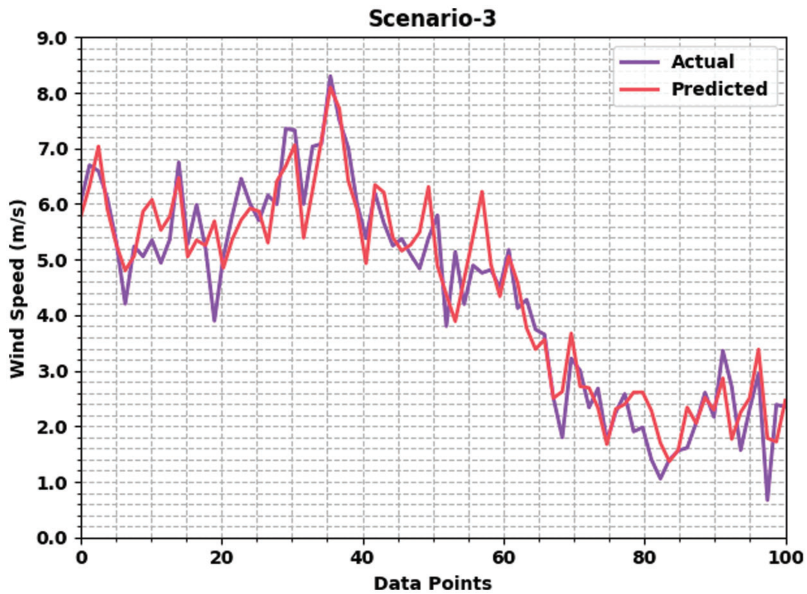

Figure 5: Actual *vs.* predicted analysis of IWSP-CSODL method under scenario 3

Table 1: Comparative analysis of IWSP-CSODL approach with existing approaches under scenario 1

Scenario-1				
Methods	MSE	MAE	MAPE (%)	R2
IWSP-CSODL	0.5318	0.4967	10.1240	0.9687
Jaya-SVM	0.6492	0.5899	11.6891	0.9468
LASSO	0.6508	0.6089	12.3410	0.9428
XGBoost	0.6699	0.6203	12.7580	0.9413
MLPR	0.6769	0.6215	12.8411	0.9204
DBN	0.7032	0.6236	12.8487	0.9116
GPR	0.7094	0.6385	13.0254	0.9064
SSAE	0.7159	0.6505	13.5843	0.8927
GrC	0.8310	0.6938	14.3853	0.8863

A detailed MAPE inspection of the IWSP-CSODL model with recent models for scenario 1 is given in Fig. 7. Here, R2 is the coefficient of determination of the MAPE, scaled between 0 and 1. The IWSP-CSODL model has gained effectual outcomes with a higher R2 value of 0.9687. At the same time, the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC models have reached reduced R2 values of 0.9468, 0.9428, 0.9413, 0.9204, 0.9116, 0.9064, 0.8927, and 0.8863 respectively.

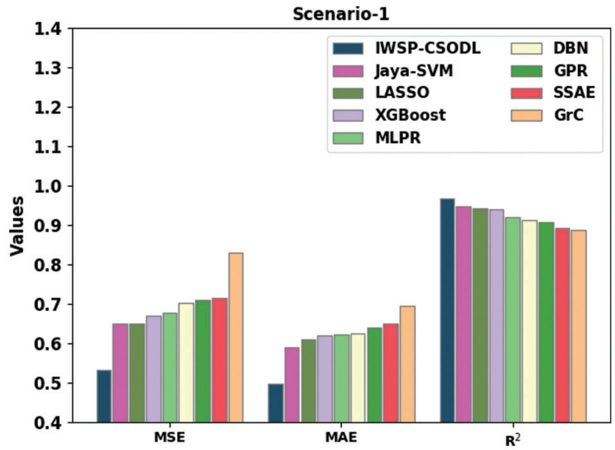

Figure 6: Comparative analysis of IWSP-CSODL approach under scenario 1

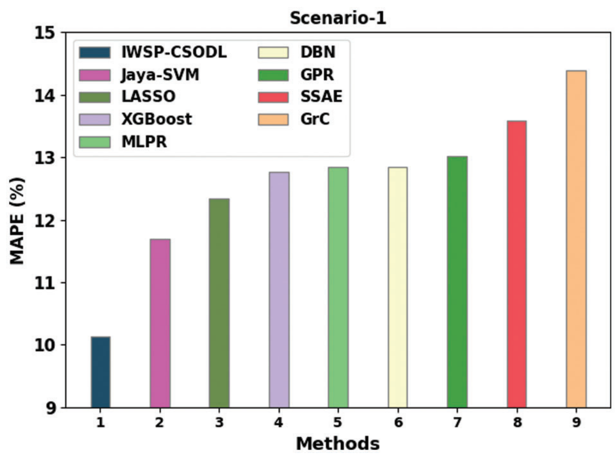

Figure 7: MAPE analysis of IWSP-CSODL approach under scenario 1

Table 2 provides an overall wind speed prediction outcome of the IWSP-CSODL model in scenario 2. Fig. 8 denotes a comparative study of the IWSP-CSODL model with other models under scenario 2. The experimental values ensured the effectual predictive outcomes of the IWSP-CSODL approach with minimal values of MSE, MAE, and MAPE. Concerning MSE, the IWSP-CSODL algorithm has offered a lower MSE of 1.0114, whereas the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC approaches have accomplished increased MSE of 1.1309, 1.1523, 1.1550, 1.1704, 1.1784, 1.2027, 1.2036, and 1.4720 correspondingly. In addition, concerning MAE, the IWSP-CSODL model has offered a lower MAE of 0.6834, whereas the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC models have accomplished increased MSE of 0.7961, 0.8125, 0.8412, 0.8756, 0.8562, 0.8209, 0.8618, and 0.9527 correspondingly. In the meantime, with respect to MAPE, the IWSP-CSODL model has provided lower MAPE of 12.5490, whereas the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC algorithms have accomplished increased MSE of 15.1714%, 16.2675%, 17.3406%, 15.8917%, 16.3558%, 15.3223%, 15.7527%, and 19.1790% correspondingly.

Table 2: Comparative analysis of IWSP-CSODL approach with existing approaches under scenario 2

Scenario-2				
Methods	MSE	MAE	MAPE (%)	R2
IWSP-CSODL	1.0114	0.6834	12.5490	0.9312
Jaya-SVM	1.1309	0.7961	15.1714	0.8955
LASSO	1.1523	0.8125	16.2675	0.8904
XGBoost	1.1550	0.8412	17.3406	0.8791
MLPR	1.1704	0.8756	15.8917	0.8708
DBN	1.1784	0.8562	16.3558	0.8646
GPR	1.2027	0.8209	15.3223	0.8511
SSAE	1.2036	0.8618	15.7527	0.8486
GrC	1.4720	0.9527	19.1790	0.8246

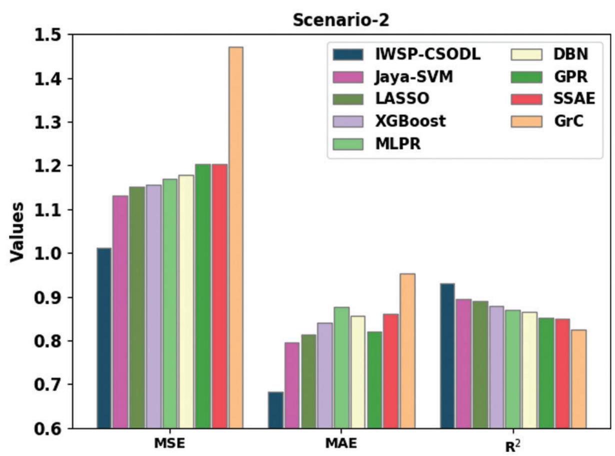

Figure 8: Comparative analysis of IWSP-CSODL approach under scenario 2

A brief MAPE inspection of the IWSP-CSODL approach with current methods on scenario 2 is given in Fig. 9. It demonstrated that the IWSP-CSODL model had obtained effectual outcomes with a higher R2 value of 0.9312 in the MAPE. Meanwhile, the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC models have reached reduced R2 values of 0.8955, 0.8904, 0.8791, 0.8708, 0.8646, 0.8511, 0.8486, and 0.8246 correspondingly.

Table 3 presents the overall wind speed prediction outcomes of the IWSP-CSODL approach on scenario 3. Fig. 10 denotes a comparative study of the IWSP-CSODL approach with other models under scenario 3. The experimental values ensured the effectual predictive outcomes of the IWSP-CSODL model with minimal values of MSE, MAE, and MAPE. With respect to MSE, the IWSP-CSODL model has offered lower MSE of 1.2654, whereas the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC algorithms have accomplished increased MSE of 1.6437, 1.7420, 1.7547, 1.7670, 1.8035, 1.8051, 1.8115, and 2.4062 correspondingly. Furthermore, concerning MAE, the IWSP-CSODL model has offered a lower MAE of 0.9185, whereas the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC models have accomplished increased MSE of 1.0179, 1.0124, 1.0714, 1.0584, 1.0431, 1.0214, 1.0667, and 1.2386 respectively. Meanwhile, concerning MAPE, the IWSP-CSODL model has provided a lower MAPE of 16.3842%, whereas the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC models have accomplished increased MSE of 19.2791%, 18.7221%, 20.2979%, 18.9103%, 18.7322%, 19.9954%, 20.3918%, and 23.5756% correspondingly.

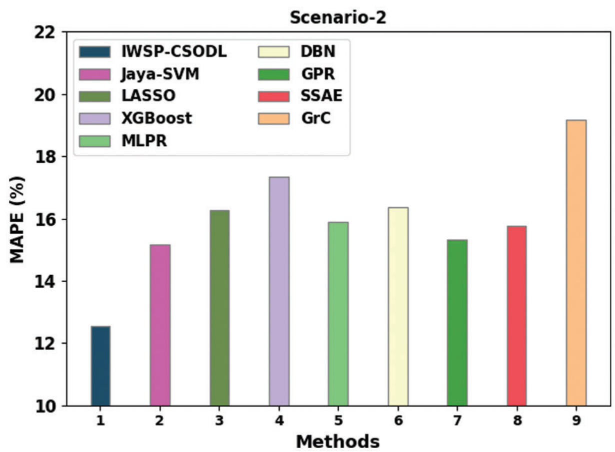

Figure 9: MAPE analysis of IWSP-CSODL approach under scenario 2

Table 3: Comparative analysis of IWSP-CSODL approach with existing approaches under scenario 3

Scenario-3				
Methods	MSE	MAE	MAPE (%)	R2
IWSP-CSODL	1.2654	0.9185	16.3842	0.8432
Jaya-SVM	1.6437	1.0179	19.2791	0.8086
LASSO	1.7420	1.0124	18.7221	0.7837
XGBoost	1.7547	1.0714	20.2979	0.8120
MLPR	1.7670	1.0584	18.9103	0.7760
DBN	1.8035	1.0431	18.7332	0.8086
GPR	1.8051	1.0214	19.9954	0.7813
SSAE	1.8115	1.0667	20.3918	0.8166
GrC	2.4062	1.2386	23.5756	0.7025

A detailed MAPE review of the IWSP-CSODL technique with recent models on scenario 3 is given in Fig. 11. It establishes that the IWSP-CSODL approach has achieved effectual outcomes with a higher R2 value of 0.8432. Meanwhile, the Jaya-SVM, LASSO, XGBoost, MLPR, DBN, GPR, SSAE, and GrC models have reached reduced R2 values of 0.8086, 0.7837, 0.8120, 0.7760, 0.8686, 0.7813, 0.8166, and 0.7025 correspondingly.

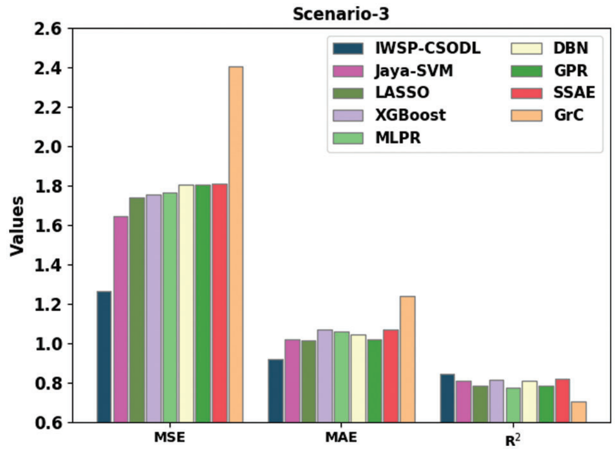

Figure 10: Comparative analysis of IWSP-CSODL approach under scenario 3

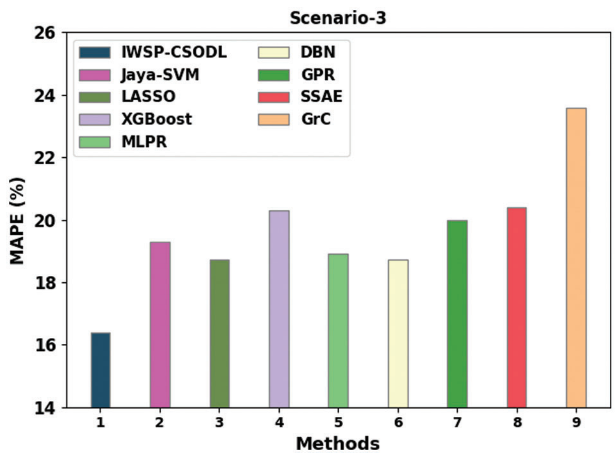

Figure 11: MAPE analysis of IWSP-CSODL approach under scenario 3

5 Conclusion

In this study, a new IWSP-CSODL model has been developed for effectual and precise wind speed forecasting. The presented IWSP-CSODL model estimates the wind speed using a hybrid deep learning and hyperparameter optimizer. In the presented IWSP-CSODL model, the CBLSTMAE model performs the prediction process. The CSO algorithm is utilized to optimize the hyperparameters related to the CBLSTMAE model, and thereby reducing MSE. The experimental validation of the IWSP-CSODL model is tested using wind series data under three distinct scenarios. The comparative study pointed out the better outcomes of the IWSP-CSODL model over other recent wind speed prediction models. In the future, the predictive performance of the IWSP-CSODL method could be boosted by the use of hybrid metaheuristic algorithms. The IWSP-CSODL method will be applied for atmospheric pressure prediction.

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