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Enhanced fault diagnosis of wind energy conversion systems using ensemble learning based on sine cosine algorithm

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Abstract

This paper investigates the problem of incipient fault detection and diagnosis (FDD) in wind energy conversion systems (WECS) using an innovative and effective approach called the ensemble learning-sine cosine optimization algorithm (EL-SCOA). The evolved strategy involves two primary steps: first, a sine-cosine algorithm is used to extract and optimize features in order to only select the most descriptive ones. Second, to further improve the capability, thereby providing the highest accuracy performance, the newly gathered dataset is introduced as input to an ensemble learning paradigm, which merges the benefits of boosting and bagging techniques with an artificial neural network classifier. The essential goal of the developed proposal is to discriminate between the diverse operating conditions (one healthy and six faulty conditions). Three potential and frequent types of faults that can affect the system behaviors including short-circuit, open-circuit, and wear-out are considered and thereby injected at diverse locations and sides (grid and generator sides) in order to evaluate the availability and performance of the proposed technique when compared to the conventional FDD methods. The diagnosis performance is analyzed in terms of accuracy, recall, precision, and computation time. The acquired outcomes demonstrate the efficiency of the suggested diagnostic paradigm compared to conventional FDD techniques (accuracy rate has been successfully achieved 98.35%).

Keywords: Wind energy conversion (WEC) systems, Fault diagnosis, Machine learning (ML), Sine-cosine optimization algorithm (SCOA), Feature selection, Feature extraction

Introduction

Year-on-year for the last few decades, wind energy has become one of the most promising, inexhaustible, green, clean, non-polluting, and sustainable energy sources. From 2011 until 2020, its production capacity expanded from 220 GW to 733 GW [1]. Unfortunately, this kind of energy is affected by several and various failures due to its complexity, which leads to the loss of its efficiency and reliability. Generators [2, 3], gearboxes [4, 5], power converters [6, 7], and blades [8, 9] are typically the most common faults. In this regard, several methods and techniques are investigated in

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the literature in order to ensure the safety, integrity, and performance of the operation of such systems [6, 10]. The study in [11] proposed two hybrid numerical weather prediction models and an artificial neural network model for wind power forecasting over extremely complicated terrain, the first model created predicts the energy output of each wind turbine directly, while the second model forecasts first the wind speed before converting it to power using a fitted power curve. By using an artificial neural network (ANN)-based distribution static compensator, the authors of [12] emphasized a new control strategy to enhance the power quality (DSTATCOM) in WECS. Mansouri et al. [13] employed a detection and diagnosis strategy for diverse incipient faults of the WECS under various states. In [14], the authors disposed of an advanced fault detection and diagnosis (FDD) approach for wind energy conversion (WEC) systems based on reduced-gaussian process regression-based random forest (RGPR-RF). Regarding the scientific community has been closely monitoring ensemble learning (EL) approaches, which mix several and numerous machine learning models to create the most optimal and best possible predictive model. The success of the ensemble model can be attributed to a variety of factors, including statistical, computational, and representation learning [15], bias-variance decomposition [16], and strength-correlation [17]. There are numerous surveys in the literature that mostly concentrate on the review of ensemble learning, such as the learning of ensemble models in classification problems [18–21]; regression problems [22, 23]; and clustering problems [24]. Indeed, an effective neural network-based ensemble technique was employed in [25]. The authors of this paper used bagging, boosting, and random subspace combination approaches together with an ensemble classifier constructed using neural network techniques. The work in [26] employed the benefits of the support vector machine, K-nearest neighbor, and the decision tree in an improved ensemble learning (EL)-based intelligent fault diagnosis paradigm that aims to guarantee the high efficiency of grid-connected photovoltaic (GCPV) systems. The initial step in data mining is known as preprocessing [27], and it entails cleaning and arranging the dataset to suit the requirements of the input for the subsequent stages.

Accordingly, one potential pre-processing step is feature selection (FS), which is a method for keeping a subset of features from a dataset that can accurately represent the data without outliers or redundancies [27]. In fact, several and numerous applications, such as data classification [28–30], data clustering [31–33], image processing [34–36], and text categorization [37, 38], deployed and utilized the FS technique. To examine the FS issue, various and several distinct versions of SCOA have been emphasized [39–46]. Besides, various optimization algorithms, for instance, the genetic algorithm (GA) [47, 48], the backtracking search algorithm (BSA) [49], the coral reef optimization (CRO) [50], the particle swarm optimization (PSO) [51], and the fruit fly optimization algorithm (FOA) [52], are introduced to keep and depict the appropriate parameters for artificial intelligent (AI) methodologies.

This work proposes an improved and effective ensemble learning approach for fault detection and diagnosis in wind conversion systems. The contribution of this paper is threefold: firstly, pre-processing data is obtained. Secondly, a sine-cosine optimization algorithm is performed in order to avoid redundant features and select and extract only the more relevant observations from the entire set of

features. Finally, the significant obtained features are fed to an ensemble learning algorithm to improve the classification performance and enhance the WECS model's reliability and ability to distinguish between the diverse operating modes. In this work, therefore, we inserted frequent, potential, and diverse types of failures: wear-out faults, open-circuit faults, and short-circuit faults, at different sides and locations (grid and generator sides) in order to examine the reliability of the developed strategy compared to the state-of-the-art methods, including artificial neural network (ANN), K-nearest neighbor (KNN), cascade forward neural network (CFNN), feed forward neural network (FFNN), generalized regression neural network (GRNN), and support vector machine (SVM). The rest of this paper is arranged as follows:

The suggested ensemble learning-based sine-cosine optimization algorithm strategy is highlighted in "Methods" section, and the concepts of each employed technique are described. The proposed technique will be tested on wind energy conversion systems in "Results and discussion" section, and the maintained results are analyzed and summarized. "Conclusion" section of this paper offers a conclusion.

Methods

EL-SCOA approach

The evolved strategy involves three major steps, including data processing and treatment, feature optimization and selection, and fault detection and diagnosis (FDD). The main goal of the suggested technique, called the ensemble learning-based sine-cosine optimization algorithm (EL-SCOA), is to improve the fault diagnosis capabilities and efficiency of WECS. Unlike conventional diagnosis methods, which apply the raw data directly, the established proposal extracts and selects the best descriptive and intensive features from the original dataset and feeds them as inputs to the classifier for diagnosis purposes. The classifier uses bagging and boosting algorithms as ensemble techniques and ANN as a baseline classifier in order to identify, classify, and discriminate between the various states that may occur in the WECS.

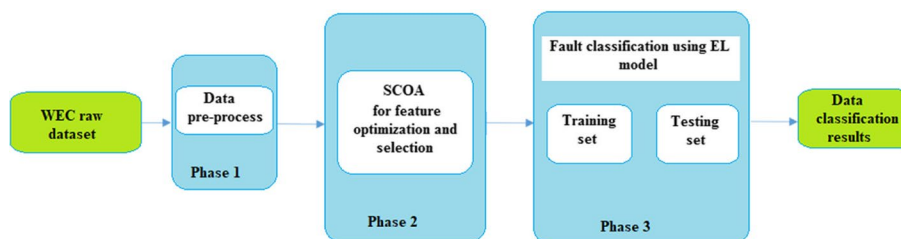The block diagram that illustrates the important steps of the evolved approach for FDD purposes is shown in Fig. 1.

Fig. 1 The steps of the proposed approach for fault diagnosis

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Input $n \times m$ data matrix X_i, $i = 1, 2, ...n$

Training phase

1. Standardize the training dataset,

2. Select the relevant features using the SCOA,

3. Introduce the required selected features as input to the proposed EL classifier,

4. Diversify faulty states using the EL classifier,

5. Establish the classification model.

Testing phase

1. Standardize the testing dataset using the mean and the variance computed in the training state,

2. Extract and select the more discriminant features using the SCOA,

3. Fed the maintained selected features as input to the EL classifier,

4. Classify the distinct conditions using the EL classifier,

5. Provide the prediction model,

6. Terminate the fault diagnosis results.

Algorithm 1. EL-SCO AlgorithmThe EL-SCOA is divided into two major categories: the training set and the testing set. The detailed descriptions are explained in Algorithm 1

Concept theoretical framework of artificial neural network (ANN)

Artificial NNs are computational models inspired by the networks of the human biological brain. These networks have gotten big attention until now [13, 48, 53]. The ANN utilizes a network pattern to generate decisions. Indeed, the input, hidden, and output layers are the three levels that make up the ANN structure. Each layer is made up of sets of nodes. The output layer provides the network response after the information has been processed by the hidden layer and received by the input layer. The number of inputs corresponds to the number of neurons in the input layer, similar to this, the number of output layer neurons corresponds to the number of ANN outputs, for instance in our work the ANN classifier is trained using WECS measurement variables ($x_1...x_m, m = 12$) as inputs, and ($N = 7$) labels as their corresponding desired outputs as depicted in Fig. 2. Nevertheless, the number of neurons in the hidden layer is determined experimentally. It consists of various experiments by varying the number of neurons in the hidden layer (10 hidden layers are employed in this study). In contrast to a complex ANN structure, a simple ANN architecture provides accurate predictions. Moreover, a signal of weight w_{ij} interconnects every two neurons of successive layers. Each neuron transfers the information to the neurons in the next layer after processing it through an activation function
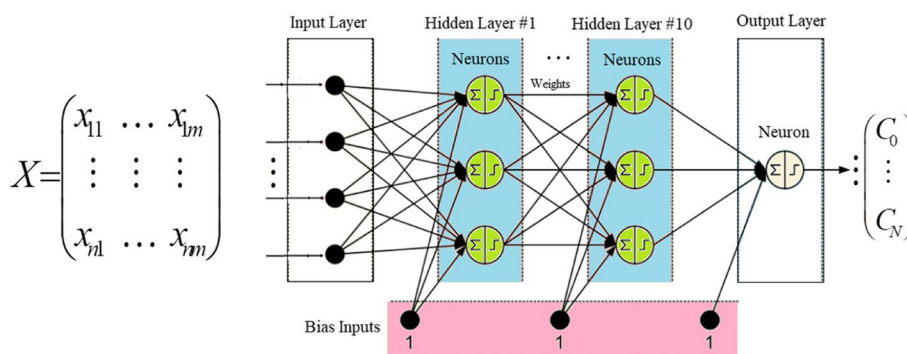
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Fig. 2 Structure ANN with *m* WECS inputs and their *N* labels' corresponding outputs

(f). The most frequently employed function is the sigmoid activation function since it is a nonlinear function that can be differentiated [54]. This function, a logistic function with a range of 0 to 1, has the following formula:

$$f = \frac{1}{1 + e^{-x}} \tag{1}$$

The weight, signal weight adjustment, prediction error, and the output of neural network equations are expressed in [55].

Ensemble learning theory

The ensemble learning methodology incorporates and combines various and several individual models in order to generate one optimal predictive model, thereby upgrading the performance and the classification results of the FDD techniques. Generally, boosting and bagging strategies are the most well-known and used in the literature.

Boosting strategy

In ensemble models, the boosting methodology, often known as a sequential ensemble [56], is used in ensemble models to improve the generalization of learning models that have weak generalizations [57]. Boosting is an ensemble technique where the predictors are created sequentially instead of independently. Indeed, boosting is based on the idea that subsequent predictors should learn from their previous errors and, accordingly, the obtained predictions become more accurate.

Bagging strategy

One of the most common techniques for generating ensemble-based algorithms is bagging [58], also named bootstrap aggregating. A bagging technique is deployed to enhance the performance of an ensemble classifier. Additionally, the intensive objective of this technique is to generate a series of independent observations with the same size and distribution as the raw dataset. Create a series of samples and generate an ensemble predictor that is more precise than the single predictor generated on the raw dataset. In fact, bagging concerns two tasks: the first is the creation of bagged observations and the transfer of each bag of observations to the base models, and the second is a technique for merging the predictions of the various predictors. Incorporating the output of the

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base predictors may differ because majority voting is utilized for classification issues and averaging is used for regression issues in order to create the ensemble output.

Concept of the sine-cosine optimization algorithm (SCOA)

The SCOA is a swarm-based optimization methodology that was first suggested by Mirjalili in 2016 [57, 58]. It is based on periodic behaviors that use the sine and cosine functions and is motivated by the transcendental function theory. Similarly to other optimization techniques, SCOA performs optimization through the use of mathematical rules. It is probable that a number of initial randomnesses possible solutions varied either away from or toward the final position (optimal solution). Some dynamic and randomized parameters highlight search exploration and exploitation via diverse optimization milestones [59]. The two phases position update equation used by the SCOA is demonstrated as follows:

$$p_{ij}^{k+1} = \begin{cases} p_{ij}^k + r_1 \times \sin(r2) \times \left| r_3 \times P_j^k - p_{ij}^k \right|, r_4 < 0.5 \\ p_{ij}^k + r_1 \times \cos(r_2) \times \left| r_3 \times P_j^k - p_{ij}^k \right|, r_4 \geq 0.5 \end{cases} \tag{2}$$

Where p denotes the position of the ith individual in the jth dimension at the $(k+1)$th iteration. P depicts the global best position in jth dimension at kth iteration. The parameter r_1 decreases linearly with the iterative process, which is utilized to ensure the balance between exploration and exploitation. The parameter r_1 is depicted as

$$r_1 = \sigma - k\frac{\sigma}{\overline{k}} \tag{3}$$

Where $\overline{k}$ indicates the maximum number of iterations, and σ is a constant number. r_2 is the random number uniformly distributed in $[0, 2\pi]$, r_3 is the random number uniformly distributed in the range $[0, 2]$, and r_4 is a random number in $[0, 1]$, which is used to switch with an equal probability between sine and cosine trigonometric functions. When $r_3 > 1$, the exchange of information between P_j^k and p_{ij}^k increases; although when $r_3 < 1$ the influence between P_j^k and p_{ij}^k is reduced. Figure 3 depicts the SCOA search mode diagram.

System description

In this research, a variable-speed wind turbine based on a squirrel cage induction generator (SCIG) is considered, as displayed in Fig. 4.

The squirrel cage induction machine (SCIG), which will be monitored and controlled by the stator-side AC/DC converter, and the grid-side DC/AC converter sub-system are the two major categories of the employed system's model. This structure permits an infinitely variable speed operation. Additionally, regardless of the machine's rotation speed, the required voltage is converted into direct current and voltage. Furthermore, for this structure, the generator grid side is based on an Insulated Gate Bipolar Transistor (IGBT), where its configuration is the same as that of the converter grid side. Table 1 illustrates the diverse properties of wind turbines.
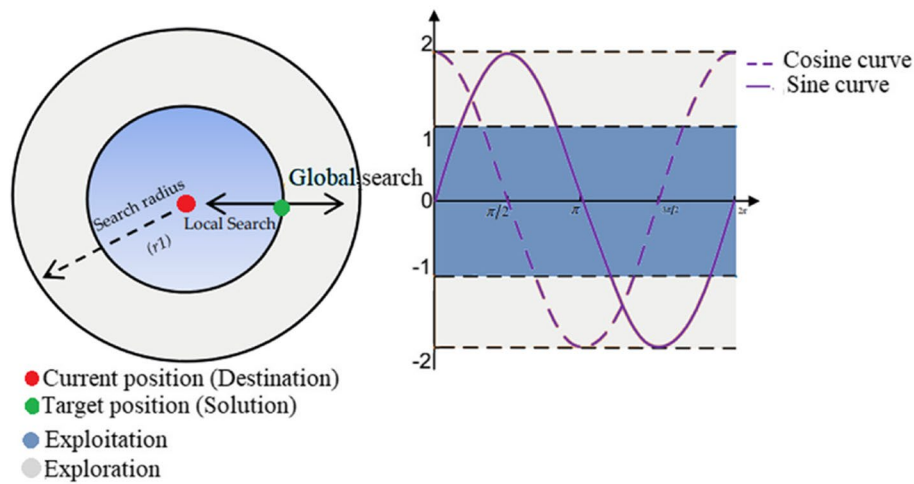
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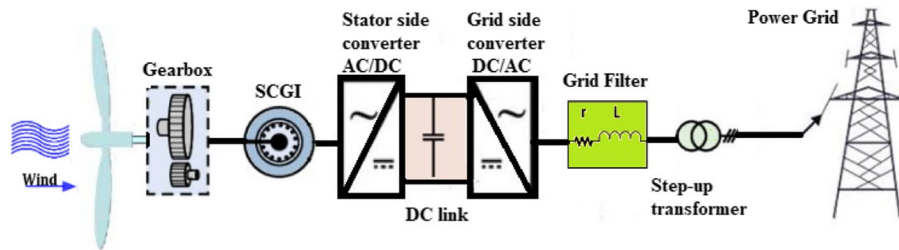**Fig. 3** Diagram of the SCOA search mode

Fig. 4 Variable speed wind turbine based on SCIG and converter topology

Table 1 Properties of wind turbine

Parameters	Nomenclature	Values
Nominal power of turbine	P_{tn}	15 *kW*
Moment of inertia of turbine	J_t	1000 *kgm²*
Stator resistance	R_s	0.087 *Ohm*
Stator leakage inductance	l_s	0.8 *mH*
Rotor resistance	R_r	0.228 *Ohm*
Rotor leakage inductance	l_r	0.8 *mH*
Magnetizing inductance	L_m	34.7 *mH*
Number of poles	P	4
Moment of inertia of generator	J_g	0.2 *kgm²*

Grid converter and generator converter are the two levels of the power conversion topology used in the wind chain. Each converter has a total of three arms. Each arm is made up of high and low IGBTs, as shown in Fig. 5.
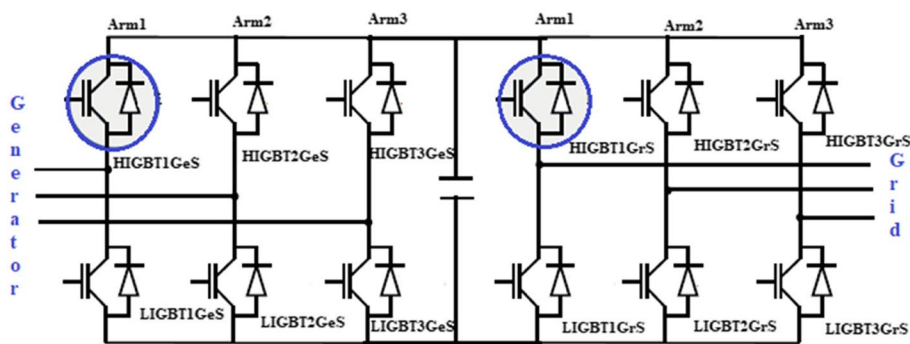
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Fig. 5 Variable speed wind turbine based on SCIG and converter topology

Table 2 Description of the diverse labeled failures injected in the WEC system

Fault side	Symbol	Fault description
Generator side	HIGBT1GeS	SC1: A short circuit fault that impacts only the first high IGBT (HIGBT) in the first arm of the converter generator side. OC1: An open circuit fault that impacts the first high IGBT in the first arm of the converter generator side. WO1: A wear-out fault that affects the first high IGBT in the first arm of the converter generator side.
Grid side	HIGBT1GrS	SC2: A short circuit fault that affects only the first high IGBT in the first arm of the converter grid side. OC2: An open circuit fault that affects only the first high IGBT in the first arm of the converter grid side. WO2: A wear-out fault that affects the first high IGBT in the first arm of the converter grid side.

Results and discussion

Data collection

In this study, we utilize data obtained from a healthy WTCS, which are then injected with several faulty scenarios: open-circuit (OC), short-circuit (SC), and wear-out. In other words, we initially considered how the system behaves in a healthy condition, and then we independently injected each faulty scenario, considering how each failure impacts and affects the system's behavior in that situation. In fact, we do not take into account the transitional regime that appears when we switch from a healthy state to a faulty condition. These faults are thoroughly described in Table 2. The internal resistance of two ohms is used to indicate the final fault (WO fault). Accordingly, each mode behavior is adequately described over 2000 10-time-lagged samples within a second-time duration with 20 KHz as the sampling frequency.

Seven operating modes of WECS are used in this study, including one healthy case (designated as C_1) and six different faulty states (C_2... C_7). Twelve measurement variables, which are used to represent these seven scenarios, are shown in further detail in Table 3.

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Table 3 Labeling, description and ranges of the measured and monitored system variables

Variables	Descriptions	Ranges
x_1	C_m: Mechanical torque (N_m)	[−346 , 731.12]
x_2	N_g: Generator speed (tr/m)	[4.01 , 966.91]
x_3	i_{sag}: Generator current phase a (A)	[−423.23 , 110.58]
x_4	i_{sbg}: Generator current phase b (A)	[−285.44 , 445.71]
x_5	i_{sd}: Generator current along d-axis (A)	[−401.49 , 362.89]
x_6	i_{sq}: Generator current along q-axis (A)	[−466.33 , 318.59]
x_7	V_{DC}: Bus voltage (V)	[−0.0034 , 0.00126]
x_8	P_{out}: Output power (W)	[−0.00127 , 0.000197]
x_9	i_{sar}: Grid current phase a (A)	[−564.29 , 349.93]
x_{10}	i_{sbr}: Grid current phase b (A)	[−404.01 , 407.88]
x_{11}	i_{sd}: Grid current along d-axis (A)	[−33.3 , 568.85]
x_{12}	i_{sq}: Grid current along q-axis(A)	[−239.54 , 347.24]

Table 4 Construction of database for fault detection and diagnosis system

Label	State	Training data	Testing data
C_1	Healthy	2000	2000
C_2	HIGBT1GeS	2000	2000
C_3		2000	2000
C_4		2000	2000
C_5	HIGBT1GrS	2000	2000
C_6		2000	2000
C_7		2000	2000

The generator variables i_{sd}, i_{sq}, and the grid variables $i_{sd}, i_{sq}, i_{sar}, i_{sbr}$ can be calculated and obtained using the Park transformation, with θ (rad),

$$\begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} = \frac{2}{3} \begin{bmatrix} cos\theta \cos\left(\theta - \frac{2\pi}{3}\right) cos(\theta + \frac{2\pi}{3}) \\ sin\theta \sin\left(\theta - \frac{2\pi}{3}\right) sin(\theta + \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{sa} \\ i_{sb} \\ i_{sc} \end{bmatrix} \tag{4}$$

Table 4 depicts the distinct operating scenarios. In both the training and testing phases, we used 50% of the observations.

Certain electrical and mechanical variables under various faulty situations are displayed in the following figures.

Evaluation metrics

Different metrics, often known as performance metrics or evaluation metrics are used to fully assess the effectiveness or quality of the model. These performance metrics enable us to evaluate how well our model performed the supplied data. In this manner, we can improve the model's performance by tuning the hyperparameters. The approved criteria are accuracy (%), which denotes the rate of samples that are correctly predicted over the total number observations. Recall (%) which denotes, in the pertinent class, the rate of positive samples correctly predicted to the observations. Precision (%) denotes the
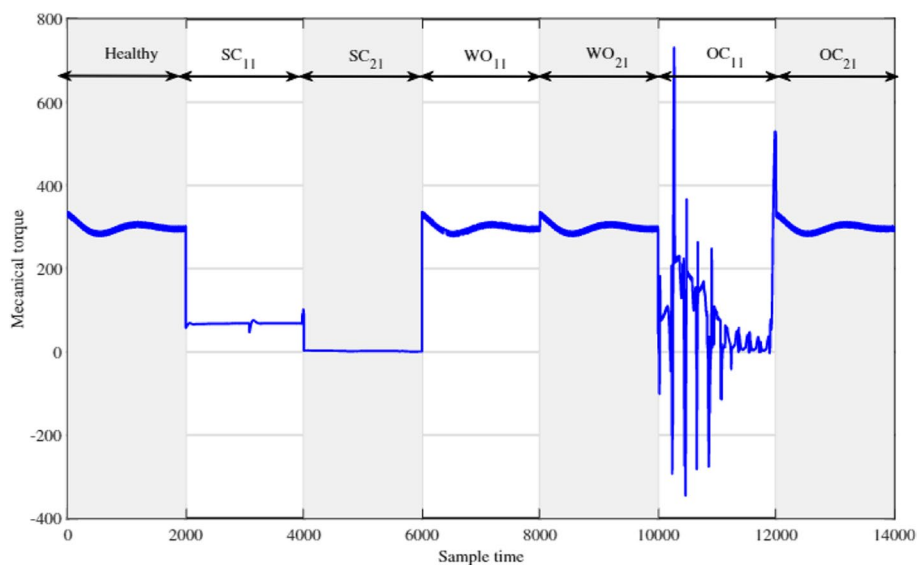
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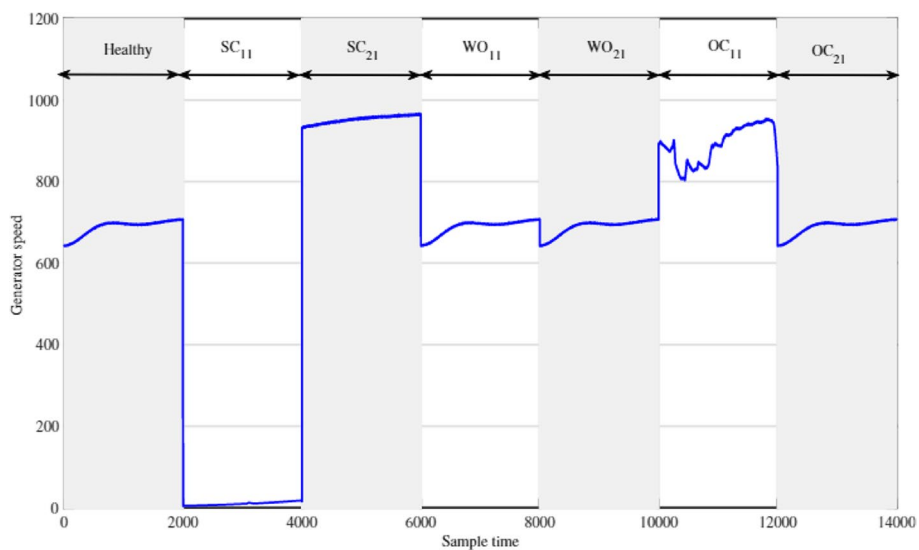**Fig. 6** Mechanical torque for different operating modes

Fig. 7 Generator speed for different operating modes

number of positive samples correctly predicted divided by the number of total predicted positive observations. Computation time (CT(s)) represents the time required to carry out the algorithm Figs. 6, 7, 8, 9 and 10.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{5}$$

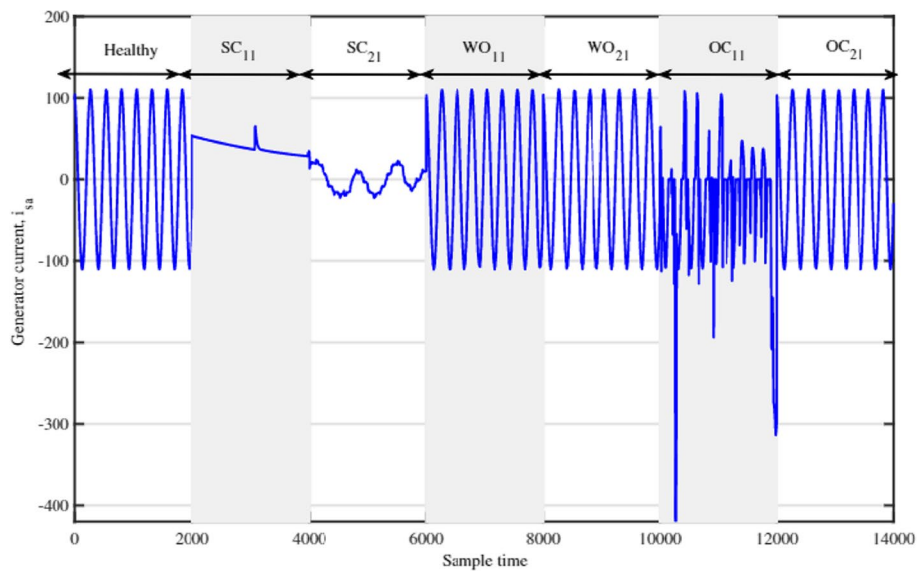$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

Fig. 8 Generator current for different operating modes
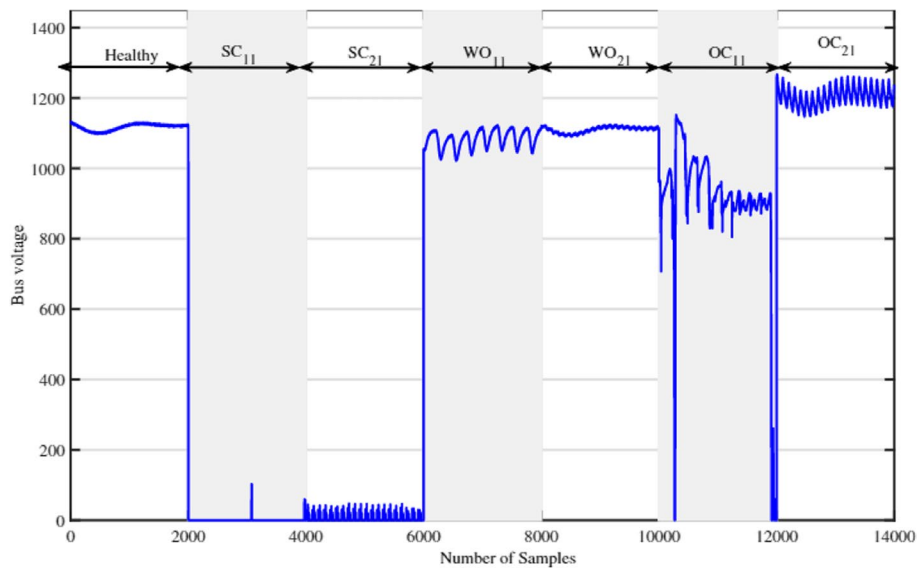
Fig. 9 Bus voltage for different operating modes

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{7}$$

Where TP (true positive) is the number of observations that are correctly identified, TN (true negative) represents the number of observations that are correctly dismissed, FP (false positive) is the number of observations that are incorrectly dismissed and FN (false negative) is the number of observations that are incorrectly identified.

Fig. 10 Grid current for different operating modes

Table 5 Performance evaluations of various classification methods
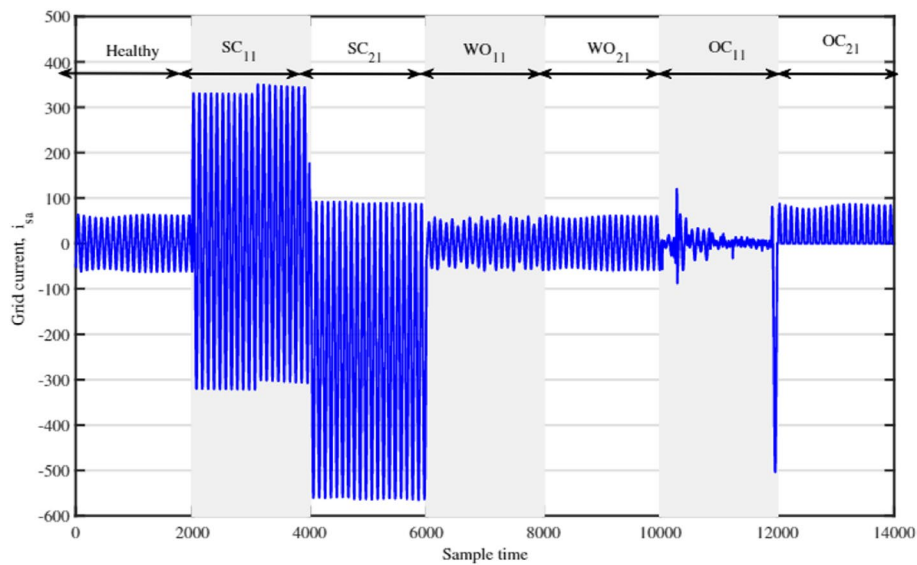
Methods	Global performance			
	Accuracy	Recall	Precision	CT(s)
EL-SCOA	98.35	98.35	98.37	12.00
EL	98.88	98.88	98.88	23.74
ANN	93.70	93.70	93.73	3.53
KNN	88.30	88.31	88.31	0.91
CFNN	97.17	97.17	97.16	8.36
FFNN	97.17	97.17	97.8	8.14
GRNN	97.06	97.06	97.06	7.06
SVM	92.14	92.14	92.16	15.69

Discussion

In order to demonstrate, and show the effectiveness of the presented approach in terms of diagnostic recall, precision, accuracy, and computation time, a number of methods, including CFNN, FFNN, ANN, GRNN, KNN, and SVM, have been employed. The diverse existing methods are modeled and tested in a MATLAB toolbox. To evaluate the overall effectiveness of the provided strategies, the accuracy was calculated using a 10-fold cross-validation metric. For the FFNN, CFNN, GRNN, and ANN, 10 hidden layers with a total of 50 hidden neurons in each layer were chosen. In order to introduce non-linearity, a sigmoid function is used in the hidden layers. The K and C parameters for SVM are set with the lowest RMSE value, and the K value for KNN is equal to 3. The maximum number of iterations for the SCOA is 100, and the number of solutions that are chosen is 10.

The comparison analysis in Table 5 showed that the proposed strategy EL, which combines the bagging and boosting strategies with the ANN classifier, performed much better than the ANN and the other methodologies in terms of accuracy (98.88%) and

Table 6 The selected features and the performance evaluations of the evolved classification strategies

Global performance						
Methods	**Number of features**	**Selected features**	**Accuracy**	**Recall**	**Precision**	**CT(s)**
EL	12	1, …12	98.88	98.88	98.88	23.74
EL-SCOA	6	2, 3, 4, 7, 8,10	98.35	98.35	98.37	12.00

Table 7 Confusion matrix for the EL-based SCOA in the testing phase

True classes	Predicted classes							Recall
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	
C_1	1858	0	0	0	142	0	0	92.90
C_2	0	2000	0	0	0	0	0	100
C_3	0	0	20	0	0	0	0	100
C_4	0	0	0	1991	900	0	0	99.55
C_5	75	0	0	100	1924	0	0	96.20
C_6	4	0	0	0	0	1996	0	99.80
C_7	0	0	0	0	0	0	2000	100
Precision	95.92	100	100	99.95	92.72	100	100	**98.35**

outperformed the other models. In spite of the fact that the suggested EL approach performs better and produces good results in terms of classification accuracy compared to conventional techniques, it still suffers from a difficult training phase and a high time complexity. To deal with this drawback, we actually employed a sine-cosine optimization algorithm (SCOA) in order to pick and select the best descriptive features and reduce the computation time, which represents a significant challenge in the fault diagnosis domain, as well as accelerate the learning and the classification tasks. As a result, the computation time is significantly decreased from 23.74 s to 12.00 s, with only a minor difference in its accuracy (by 0.53%). The inefficient KNN and SVM classification outcomes are attributable to the direct usage of raw data, demonstrating the success of the suggested approach that selects the more significant features before performing the classification task. Six features (out of 12) of the developed EL-SCOA strategy were best selected, as shown in the following table (Table 6).

Table 7 illustrates the obtained testing classification outcomes of the diverse classes by the use of a confusion matrix (CM) to further demonstrate the effectiveness of the evolved methodology. Indeed, the samples that were successfully labeled to the healthy condition (*C*1) and the various faulty operating states (*C*2 to *C*7) as well as the samples that were incorrectly labeled, are both displayed in this matrix. Specifically, the *X* and *Y* axes highlight the true classes and the projected conditions, respectively.

Table 7 demonstrates that the EL-based SCOA strategy correctly identifies the 2000 observations from the 2000 true positives for the conditions operating modes (C_2, C_3, and C_7), indicating that these modes are correctly classified and there was no misclassification. However, there is a misclassification for the healthy state (C_1), faulty modes 3 (C_4), 4 (C_5), and 5 (C_6), as evidenced by the classification of 142 observations from the

healthy class as the class (C_5), 9 observations from the class (C_4) as the class (C_5), and 4 samples from the class (C_6) as the class (C_1).

Conclusions

This paper developed an enhanced fault detection and diagnosis approach called an ensemble learning-based sine-cosine optimization algorithm (EL-SCOA) for wind energy conversion (WEC) systems. The presented methodology was addressed so that the sine-cosine algorithm is proposed in order to optimize, select, and extract the most informative features from the raw data, where the maintained selected features are fed to the classification technique for diagnosis purposes. The classification method incorporates bagging and boosting as ensemble methods and an ANN as a baseline classifier. The proposed paradigm attempted to discriminate between various operating states (short circuit, open circuit, and wear-out faults) introduced at various locations and sides (generator and grid sides). As compared to other existing methods including ANN, KNN, CFNN, FFNN, GRNN, and SVM, the experimental outcomes show that the suggested strategy performs very well. As a result, the effectiveness of the suggested technique inspires us to further examine its computation time and memory storage in future research. In order to simultaneously improve diagnosis accuracy and decrease WEC system execution time, a strategy that combines data size reductions and the aforementioned technique will be proposed.

Abbreviations

SCA	Sine cosine algorithm
SCOA	Sine cosine optimization algorithm
EL	Ensemble learning
WECS	Wind energy conversion system
WT	Wind turbine
FDD	Fault detection and diagnosis
FE	Feature extraction
FS	Feature selection
ANN	Artificial neural network
NN	Neural network
RNN	Recurrent NN
FFNN	Feed-forward NN
CFNN	Cascade forward NN
GRNN	Generalized regression NN
RF	Random forest
KNN	K-nearest neighbors
SC	Short circuit
OC	Open circuit
WO	Wear out
SVM	Support vector machine
CT	Computation time
CM	Confusion matrix

Authors' contributions
KA wrote the original draft and worked on the software. KD worked on the software. MM and MH defined the methodology, reviewed, and edited the manuscript. Kais KB and HN supervised the work. All authors read and approved the final manuscript.

Availability of data and materials
Data will be made available on request.

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Declarations

Competing interests
The authors declare that they have no competing interests.

References

1. Murgas B, Henao A, Guzman L (2021) Evaluation of investments in wind energy projects, under uncertainty. state of the art review. Appl Sci 11(21):10213
2. Singh G, Sundaram K (2022) Methods to improve wind turbine generator bearing temperature imbalance for onshore wind turbines. Wind Eng 46(1):150–159
3. Xu Y, Nascimento NMM, de Sousa PHF, Nogueira FG, Torrico BC, Han T, Jia C, Rebouças filho PP (2021) Multi-sensor edge computing architecture for identification of failures short-circuits in wind turbine generators. Appl Soft Comput 101:107053
4. López-Uruñuela FJ, Fernandez-Diaz B, Pagano F, López-Ortega A, Pinedo B, Bayón R, Aguirrebeitia J (2021) Broad review of "white etching crack" failure in wind turbine gearbox bearings: Main factors and experimental investigations. Int J Fatigue 145:106091
5. Wang L, Zhang Z, Long H, Xu J, Liu R (2016) Wind turbine gearbox failure identification with deep neural networks. IEEE Transact Industrial Inform 13(3):1360–1368
6. Kouadri A, Hajji M, Harkat M-F, Abodayeh K, Mansouri M, Nounou H, Nounou M (2020) Hidden markov model based principal component analysis for intelligent fault diagnosis of wind energy converter systems. Renew Energ 150:598–606
7. Xiao C, Liu Z, Zhang T, Zhang X (2021) Deep learning method for fault detection of wind turbine converter. Appl Sci 11(3):1280
8. Ravikumar K, Subbiah R, Ranganathan N, Bensingh J, Kader A, Nayak SK (2020) A review on fatigue damages in the wind turbines: Challenges in determining and reducing fatigue failures in wind turbine blades. Wind Eng 44(4):434–451
9. Mishnaevsky L Jr (2022) Root causes and mechanisms of failure of wind turbine blades: Overview. Materials. 15:2959
10. Fezai R, Dhibi K, Mansouri M, Trabelsi M, Hajji M, Bouzrara K, Nounou H, Nounou M (2020) Effective random forest-based fault detection and diagnosis for wind energy conversion systems. IEEE Sensors J 21(5):6914–6921
11. Donadio L, Fang J, Porté-Agel F (2021) Numerical weather prediction and artificial neural network coupling for wind energy forecast. Energies 14(2):338
12. Irfan MM, Malaji S, Patsa C, Rangarajan SS, Hussain SS (2022) Control of dstatcom using ann-bp algorithm for the grid connected wind energy system. Energies 15(19):6988
13. Mansouri M, Dhibi K, Nounou H, Nounou M (2022) An effective fault diagnosis technique for wind energy conversion systems based on an improved particle swarm optimization. Sustainability 14(18):11195
14. Mansouri M, Fezai R, Trabelsi M, Nounou H, Nounou M, Bouzrara K (2021) Reduced gaussian process regression based random forest approach for fault diagnosis of wind energy conversion systems. IET Renew Power Gener 15(15):3612–3621
15. Dietterich TG (2000) Ensemble methods in machine learning. Multiple Classifier Systems: First International Workshop, MCS 2000 Cagliari, Italy, June 21–23, 2000 Proceedings 1. Springer, Cagliari, Italy, pp 1–15
16. R. Kohavi, D. H. Wolpert, et al., (1996). Bias plus variance decomposition for zero-one loss functions, in: ICML, Vol. 96, Citeseer, 275–83.
17. Breiman L (2001) Random forests. Machine Learn 45:5–32
18. Zhao J, Gao X, Yang (2005). A survey of neural network ensembles, in: 2005 international conference on neural networks and brain, vol 1. IEEE, Beijing, pp 438–442
19. Rokach L (2010) Ensemble-based classifiers. Artif Intell Rev 33:1–39
20. Gopika D, Azhagusundari B (2014) An analysis on ensemble methods in classification tasks
21. Yang P, Hwayang Y, Zhou BB, Zomaya AY (2010) A review of ensemble methods in bioinformatics. Current Bioinformatics. 5(4):296–308
22. Mendes-Moreira J, Soares C, Jorge AM, Sousa JFD (2012) Ensemble approaches for regression: a survey. ACM Comput Surveys (csur) 45(1):1–40
23. Ren Y, Suganthan P, Srikanth N (2015) Ensemble methods for wind and solar power forecasting—a state-of-the-art review. Renew Sustain Energ Rev 50:82–91
24. Vega-Pons S, Ruiz-Shulcloper J (2011) A survey of clustering ensemble algorithms. Int J Pattern Recogn Artif Intell 25(03):337–372
25. Dhibi K, Mansouri M, Bouzrara K, Nounou H, Nounou M (2022) Reduced neural network based ensemble approach for fault detection and diagnosis of wind energy converter systems. Renew Energ. 194:778–787
26. Dhibi K, Mansouri M, Bouzrara K, Nounou H, Nounou M (2021) An enhanced ensemble learning-based fault detection and diagnosis for grid-connected pv systems. IEEE Access 9:155622–155633
27. Guyon I, Elisseeff A (2003) An introduction to variable and feature selection. J Machine Learn Res. 3:1157–1182
28. Hua J, Tembe WD, Dougherty ER (2009) Performance of feature-selection methods in the classification of high-dimension data. Pattern Recogn 42(3):409–424
29. Gómez-Verdejo V, Verleysen M, Fleury J (2009) Information-theoretic feature selection for functional data classification. Neurocomputing 72(16–18):3580–3589

30. R. Z. Al-Abdallah, A. S. Jaradat, I. A. Doush, Y. A. Jaradat. (2017) .A binary classifier based on firefly algorithm. Jordan J Comput Inform Technol (JJCIT); 3(3):172-185
31. Liu H, Yu L (2005) Toward integrating feature selection algorithms for classification and clustering. IEEE Transact Knowledge Data Eng 17(4):491–502
32. Boutemedjet S, Bouguila N, Ziou D (2008) A hybrid feature extraction selection approach for high-dimensional non-gaussian data clustering. IEEE Transact Pattern Analysis Machine Intell 31(8):1429–1443
33. ElMustafa S, Jaradat A, Doush IA, Mansour N (2017) Community detection using intelligent water drops optimisation algorithm. Int J Reason-based Intell Syst 9(1):52–65
34. Huang K, Aviyente S (2008) Wavelet feature selection for image classification. IEEE Transact Image Process 17(9):1709–1720
35. Chen B, Chen L, Chen Y (2013) Efficient ant colony optimization for image feature selection. Sign Process 93(6):1566–1576
36. Sawalha R, Doush IA (2012) Face recognition using harmony search-based selected features. Int J Hybrid Inform Technol 5(2):1–16
37. Shang W, Huang H, Zhu H, Lin Y, Qu Y, Wang Z (2007) A novel feature selection algorithm for text categorization. Exp Syst Appl 33(1):1–5
38. Zheng Z, Wu X, Srihari R (2004) Feature selection for text categorization on imbalanced data. ACM Sigkdd Explor Newslett 6(1):80–89
39. Neggaz N, Ewees AA, Abd Elaziz M, Mafarja M (2020) Boosting salp swarm algorithm by sine cosine algorithm and disrupt operator for feature selection. Exp Syst Appl 145:113103
40. Sindhu R, Ngadiran R, Yacob YM, Zahri NAH, Hariharan M (2017) Sine–cosine algorithm for feature selection with elitism strategy and new updating mechanism. Neural Comput Appl 28:2947–2958
41. Eid MM, El-kenawy E-SM, Ibrahim A (2021) A binary sine cosine modified whale optimization algorithm for feature selection. 2021 National Computing Colleges Conference (NCCC). IEEE, Taif, Saudi Arabia, pp 1–6
42. Hussain K, Neggaz N, Zhu W, Houssein EH (2021) An efficient hybrid sine-cosine harris hawks optimization for low and high-dimensional feature selection. Exp Syst Appl 176:114778
43. M. E. Abd Elaziz, A. A. Ewees, D. Oliva, P. Duan, S. Xiong. (2017). A hybrid method of sine cosine algorithm and differential evolution for feature selection, in: Neural Information Processing: 24th International Conference, ICONIP 2017, Guangzhou, China, November 14–18, 2017, Proceedings, Part V 24, Springer:145–155.
44. Abualigah L, Dulaimi AJ (2021) A novel feature selection method for data mining tasks using hybrid sine cosine algorithm and genetic algorithm. Cluster Comput 24:2161–2176
45. Abd Elaziz M, Oliva D, Xiong S (2017) An improved opposition-based sine cosine algorithm for global optimization. Expert Syst Appl 90:484–500
46. R. Sindhu, R. Ngadiran, Y. M. Yacob, N. A. Hanin Zahri, M. Hariharan, K. Polat. (2019). A hybrid sca inspired bbo for feature selection problems. Math Problems Eng; 2019.
47. Dhunny A, Timmons D, Allam Z, Lollchund M, Cunden T (2020) An economic assessment of near-shore wind farm development using a weather research forecast-based genetic algorithm model. Energy 201:117541
48. Hichri A, Hajji M, Mansouri M, Abodayeh K, Bouzrara K, Nounou H, Nounou M (2022) Genetic-algorithm-based neural network for fault detection and diagnosis: Application to grid-connected photovoltaic systems. Sustainability 14(17):10518
49. Kartite J, Cherkaoui M (2017) Improved backtracking search algorithm for renewable energy system. Energy Procedia 141:126–130
50. Salcedo-Sanz S, Gallo-Marazuela D, Pastor-Sánchez A, CarroCalvo L, Portilla-Figueras A, Prieto L (2014) Offshore wind farm design with the coral reefs optimization algorithm. Renew Energy. 63:109–115
51. He Z, Chen Y, Shang Z, Li C, Li L, Xu M (2019) A novel wind speed forecasting model based on moving window and multi-objective particle swarm optimization algorithm. Appl Math Model 76:717–740
52. Zhang Q, Qian H, Chen Y, Lei D (2020) A short-term traffic forecasting model based on echo state network optimized by improved fruit fly optimization algorithm. Neurocomputing 416:117–124
53. Hajji M, Yahyaoui Z, Mansouri M, Nounou H, Nounou M (2023) Fault detection and diagnosis in grid-connected pv systems under irradiance variations. Energ Rep 9:4005–4017
54. Hippert HS, Pedreira CE, Souza RC (2001) Neural networks for short term load forecasting: a review and evaluation. IEEE Transact Power Syst 16(1):44–55
55. Jamii J, Mansouri M, Trabelsi M, Mimouni MF, Shatanawi W (2022) Effective artificial neural network-based wind power generation and load demand forecasting for optimum energy management. Front Energy Res. 10:898413
56. Ganaie MA, Hu M, Malik A, Tanveer M, Suganthan P (2022) Ensemble deep learning: a review. Eng Appl Artificial Intell 115:105151
57. Zhang W, Jiang J, Shao Y, Cui B (2020) Snapshot boosting: a fast ensemble framework for deep neural networks. Sci China Inform Sci 63:1–12
58. Breiman L (1996) Bagging predictors. Machine Learn 24:123–140
59. Shang C, Zhou T-T, Liu S (2022) Optimization of complex engineering problems using modified sine cosine algorithm. Sci Rep 12(1):20528

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