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A Hybrid Algorithm Based on Social Engineering and Artificial Neural Network for Fault Warning Detection in Hydraulic Turbines

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Abstract: Hydraulic turbines constitute an essential component within the hydroelectric power generation industry, contributing to renewable energy production with minimal environmental pollution. Maintaining stable turbine operation presents a considerable challenge, which necessitates effective fault diagnosis and warning systems. Timely and efficient fault w arnings are particularly vital, as they enable personnel to address emerging issues promptly. Although backpropagation (BP) networks are frequently employed in fault warning systems, they exhibit several limitations, such as susceptibility to local optima. To mitigate this issue, this paper introduces an improved social engineering optimizer (ISEO) method aimed at optimizing BP networks for developing a hydraulic turbine warning system. Experimental results reveal that the ISEO-BP-based approach offers a highly effective fault warning system, as evidenced by superior performance metrics when compared to alternative methods.

Keywords: automated fault warning; BP neural network; artificial intelligence; optimization

MSC: 93-10

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1. Introduction

In the era of Industry 4.0, there is a growing need for enhanced equipment reliability and responsiveness [1]. Hydraulic turbines, serving as vital power-generating equipment in hydroelectric power plants, play a critical role in determining overall operational quality and efficiency [2]. Consequently, ensuring high-quality turbine operation and avoiding instability during the manufacturing process is imperative. Fault diagnosis and warning systems are essential tools for addressing this challenge [3]. Fault diagnosis involves identifying faults when equipment behavior exceeds acceptable thresholds, enabling relevant personnel to respond appropriately [4]. In contrast, fault warning aims to forecast future equipment behavior and estimate potential failure moments, thus aiding decision-making processes related to maintenance concerns [5,6].

The literature review highlights the significance of fault warnings in averting failures and minimizing costs, as compared to fault diagnosis. Numerous studies have focused on devising effective fault warning models utilizing artificial neural networks and optimization algorithms [7]. For instance, Scalabrini et al. [8] employed accelerometers to gauge vibrations, and artificial neural networks to predict motor failure timing, resulting in reduced operational costs and complexity. Gao et al. [9] suggested an adaptive deep belief network for early warnings in the electric vehicle charging process to enhance safety. Cai et al. [10] developed a distribution network fault warning model using the XGBoost method. Meanwhile, Sun et al. [11] proposed a technique for analyzing fault warnings of critical transmission components in wind turbines by integrating a nonlinear method, feature reduction method, and metric learning. They conducted experiments with engineering examples, demonstrating the importance of their proposed method in providing warnings for wind turbine equipment [11]. Additionally, Cui et al. [12] created an air compressor fault warning model using principal component analysis and the BP method. Li et al. [13] enhanced the performance of a convolutional neural network utilizing a particle swarm optimization (PSO) algorithm for fault warnings in synchronous generators. Concurrently, Liu et al. [14] employed an improved long-short-term memory (LSTM) model for early warning of axle box bearing faults. Wang et al. [15] utilized a BP neural network for early warning of distribution transformer faults, while Chen et al. [16] improved a BP neural network with a genetic algorithm (GA) for fault warning in wind turbine pitch systems. Ma et al. [17] constructed a BP neural network model for crusher fault diagnosis, and Ling et al. [18] applied a GA-optimized BP neural network for generator fault diagnosis. Zhang et al. [19] developed a BP neural network model for electric vehicle charging safety warnings using an enhanced grey wolf optimization algorithm. Lee et al. [20] proposed a neural network employing PSO for fault diagnosis. Sun et al. [21] examined the thermal runaway warning of new energy vehicle batteries and developed a data-driven warning system. Yuan et al. [22] investigated a fault warning strategy for pitch motors, employing an echo state network to predict the motor's temperature and subsequently using an exponentially weighted moving average technique to set alarm limit lines for each parameter. Huo et al. [23] studied a mechanical fault detection and warning method based on adversarial autoencoder. Mu et al. [24] conducted research and analysis on transmission grid cascade fault warning localization and developed a warning framework using long and short neural networks. Zhou et al. [25] created a BP neural network-based early warning algorithm for thermal fault diagnosis in electrical equipment, demonstrating better prediction accuracy. Yao et al. [26] combined clustering and classification methods to develop a fault warning system for steam turbines. He et al. [27] developed a multi-module emerging fault warning method for thermal power plants, suitable for scenarios with few operational samples. Wang [28] proposed a wind turbine fault warning method based on a residual self-encoder network to effectively avoid gradient disappearance issues. Lastly, Zhang et al. [29] enhanced neural networks with a cuckoo optimization algorithm for industrial equipment fault warning.

After conducting a thorough review and analysis of the relevant literature, we have arrived at the following conclusions:

- The BP neural network is a widely utilized approach for fault warning due to its conciseness, effectiveness, and practicality compared to alternative methods. However, during the network's initialization, both weights and thresholds are generated randomly and subsequently updated using the gradient descent method. The sensitivity of the BP neural network to initial weights implies that varying weight initialization can result in divergent convergence of the BP algorithm, which can significantly impact the efficiency and quality of the BP neural network. Thus, it is crucial to optimize the initial weights and threshold selection method of the BP neural network to maximize performance and enhance fault-warning outcomes.
- Metaheuristic algorithms have gained recognition as potent tools for optimizing BP neural networks, thanks to their straightforward parameter adjustment and exceptional merit-seeking capability [28–30]. The integration of metaheuristic algorithms with BP neural networks has become a significant research topic, as it can yield enhanced performance and superior outcomes in diverse applications related to fault warning and diagnosis.
- While numerous combinations of BP with GA, COA, PSO, and various traditional algorithms exist, to the best of our knowledge, no study has assessed the performance of the Social Engineering Optimizer SEO within this research domain.

- The "No Free Lunch" theorem in the optimization community posits that no universal optimization algorithm consistently outperforms all other algorithms across every optimization problem [31]. Consequently, it is vital to persistently explore the application of diverse optimization algorithms in novel areas and refine them to address their limitations and augment their performance on specific issues. This notion holds particular significance for metaheuristic algorithms, which have demonstrated immense potential in optimizing intricate problems but necessitate meticulous selection and tuning of parameters to attain favorable results. By continuously advancing and enhancing these algorithms, we can further boost their performance and broaden their application scope across various fields, including fault warning and neural network optimization.

In order to address the aforementioned research gaps, this paper introduces an Improved Social Engineering Optimizer (ISEO) to establish a hybrid model referred to as ISEO-BP. We apply this model to hydraulic turbine fault warning with the aim of better aligning hydraulic turbine maintenance with industrial development requirements, while simultaneously ensuring optimal operational efficiency and quality.

- First, we propose improvements to traditional SEO to overcome its limitations and enhance its performance. These improvements include new search operators to create a better balance between the exploration and exploitation phases.
- Second, we introduce a novel approach by combining SEO with the BP neural network, which expands the application area of SEO and enhances its effectiveness in solving complex problems.
- Third, we propose a new fault warning method called ISEO-BP, specifically designed for hydraulic turbines. Our method analyzes various failure modes of hydraulic turbines and provides relevant personnel with timely information to choose appropriate maintenance strategies. We also propose an application strategy for using this method to address equipment failure warning in other industries.
- Finally, we validate the effectiveness of our proposed method through real-world industrial case studies.

In conclusion, this paper discusses the development of a fault warning system for hydraulic turbines in hydroelectric power plants. With the increasing need for reliable and responsive equipment, fault diagnosis and warning are crucial tools to ensure efficient operation. Fault diagnosis identifies faults when the equipment's behavior exceeds acceptable conditions, while fault warning predicts future behavior to prevent failures and facilitate maintenance decisions. Compared to fault diagnosis, fault warning, as a mode of prior prevention, is particularly important. However, there is a slight lack of research on fault warning strategies. Additionally, BP neural networks, an essential tool in this field, have significant shortcomings, and metaheuristic algorithms that serve to improve these shortcomings must be given importance.The paper explores the use of a BP neural network as a fault warning method, highlighting its advantages and limitations, and proposes optimizing the initial weights and threshold selection of the BP neural network using the recently developed SEO algorithm. The proposed method, called ISEO-BP, is applied to hydraulic turbine fault warning and compared with other existing methods. This paper contributes to the application of the SEO algorithm in new areas and demonstrates that the proposed method can effectively improve the efficiency and quality of hydraulic turbine fault warning.

The structure of the remainder of the paper is organized as follows: In Section 2, we introduce ISEO-BP, which is an improvement of SEO that is integrated with BP networks. Section 3 demonstrates the effectiveness of ISEO by applying it to a hydroelectric power plant turbine case and proposing a turbine fault warning strategy. In Section 4, we compare ISEO-BP with other advanced methods to further illustrate its effectiveness. Finally, in Section 5, we conclude the paper with a summary, limitations, and suggestions for future research.

2. Proposed Solution Method

In this paper, we propose an ISEO-BP method for hydraulic turbine fault warning. Here, we first introduce the BP neural network (Section 2.1), followed by a description of the main SEO framework, and our improvements to SEO (Section 2.2), and finally, we describe the detailed flow of our proposed INGO-BP (Section 2.3).

2.1. BP Neural Network

The BP neural network is a well-established multilayer neural network that has been demonstrated to be effective in numerous applications [32]. It comprises three primary components: the input layer, hidden layer, and output layer. A key characteristic of this network is its forward signal transmission and backward error propagation, which enables continuous adjustments of network weights to achieve training objectives and closely approximate desired outputs. A schematic representation of a typical BP neural network is provided in Figure 1. The weight and threshold adjustment formulas for the BP neural network are given by Equations (1) and (2), respectively.

$$w_{ij}(u+1) = w_{ij}(t) + \varepsilon\delta_j H_j \tag{1}$$

$$\mu_j(u+1) = \mu_j(t) + \eta\sigma_j \tag{2}$$

where w and μ denote the weights and thresholds, respectively; u denotes the number of BP network iterations; ε and η denotes the learning parameter; H denotes the jth hidden layer node; δ_j and σ_j denote the error signal values of the nodes, respectively.

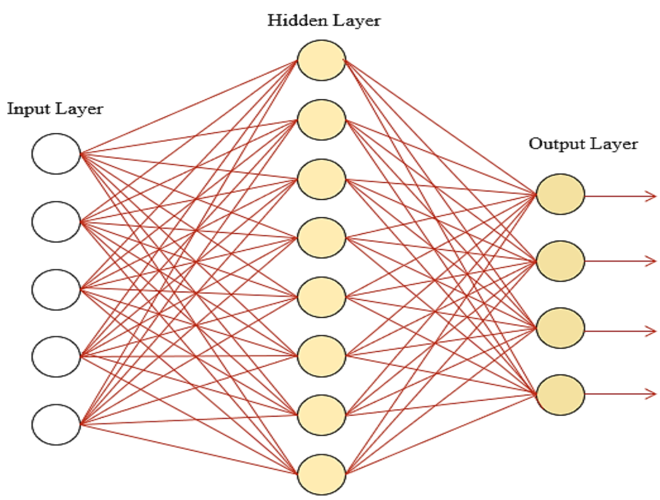

Figure 1. A typical BP neural network.

The BP neural network comprises several essential steps, including initialization, forward propagation, error calculation, backpropagation, and iterative repetition of these steps. In the initial stage of training, the network randomly assigns weights and biases to its neurons. Input data is subsequently passed through the network, where a series of weighted and nonlinear activation functions generate an output. This output is then compared to the actual label, enabling the calculation of an error.

During the backpropagation phase, the gradient of each neuron is determined using the chain rule. Subsequently, weights and biases are updated, starting from the output layer and progressing backward. These steps are iteratively repeated until the error attains an acceptable level or a pre-determined number of iterations is reached. Figure 2 offers a visual depiction of the processes involved in a BP neural network.

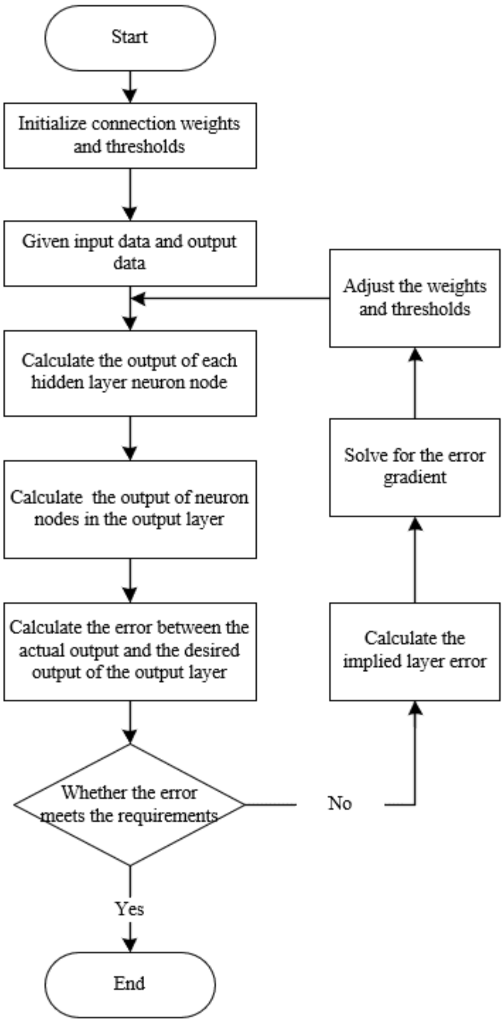

Figure 2. BP neural network flow chart.

2.2. ISEO

SEO was initially introduced by Fathollahi-Fard et al. [33] as a metaheuristic algorithm inspired by social engineering theory. Social engineering involves obtaining individuals' personal information through various techniques, which is then used to influence or coerce them into complying with the demands of social engineers [34]. SEO presents a simpler and more efficient alternative to other metaheuristics, with only four main steps and three straightforward parameters that are easy to understand and implement.

Numerous experiments have demonstrated that SEO surpasses other well-established and recently developed metaheuristics in terms of solution accuracy, robustness, and efficiency [35]. Nevertheless, since SEO heavily relies on random initial solutions, it may result in suboptimal solutions and local optima. To address this limitation, we propose a novel strategy called positive cosine optimization, which enhances SEO's initial solution formation process to improve its performance. In this paper, we present the Improved SEO (ISEO) algorithm, which combines positive cosine optimization with the original SEO algorithm. The ISEO algorithm is tested on various benchmark functions and engineering examples, showcasing its effectiveness and efficiency in solving complex optimization problems.

In summary, this paper introduces a novel optimization algorithm named ISEO, which merges the advantages of SEO with positive cosine optimization. The proposed algorithm provides a more efficient and accurate method for solving optimization problems, holding significant potential for practical applications across various fields. The following sections contain a detailed description of the ISEO proposed in this paper.

2.2.1. Sine Cosine Algorithm

The Sine Cosine Optimization Algorithm (SCA) was proposed by Mirjalili et al. in 2016 [34]. In this algorithm, the solution fluctuates either outward or toward the optimal solution based on the mathematical model of sine and cosine functions. The algorithm employs multiple random and adaptive variables to calculate the current solution location, allowing it to search different regions in the solution space effectively. By adeptly avoiding local optima and converging to the global optimum, SCA demonstrates its efficacy. Inspired by these properties, we introduce SCA's update strategy in the initial solution generation process of SEO. The corresponding formulas are depicted in Equations (3) and (4).

$$X_i^j(t+1) = X_i^j(t) + r_1 \cdot \sin(r_2) \cdot \left| r_3 P^j(t) - X_i^j(t) \right| \tag{3}$$

$$X_i^j(t+1) = X_i^j(t) + r_1 \cdot \cos(r_2) \cdot \left| r_3 P^j(t) - X_i^j(t) \right| \tag{4}$$

where t denotes the current number of iterations; $X_i^j(t)$ denotes the component of the position of individual i in the jth dimension at the tth iteration; r_1, r_2, r_3 are random parameters; $P^j(t)$ denotes the component of the optimal candidate solution of the candidate solution set in the jth dimension at the tth selection.

The selection of the SCA optimization strategy is performed with the probability of generating a random number P. When $P > 0.5$, Equation (1) is selected for individual updating, and vice versa, Equation (2) is selected.

2.2.2. ISEO Main Framework

Combining the SCA proposed in the previous section with traditional SEO steps, our ISEO framework is as follows.

Step 1: Initialize the attacker and the defender.

The first step of SEO is to form an attacker and a defender by first generating two random solutions [33], after which the solution with better fitness is selected as the attacker and the other is selected as the defender.

It should be noted that in order to better improve the quality of the initial solution and compensate for the disadvantage that SEO is easy to fall into local optimization, we integrate the optimization process of the SCA in the first step of the algorithm. In our proposed ISEO, attackers and defenders are not generated according to random solutions, and we set an inner loop number *ymaxit*. First, *npop* initial solutions are formed randomly, and according to the SCA, continuously optimized for the initial solution, and the selection of attackers and defenders is performed after the operation stops. The one with the highest adaptation is chosen as the attacker and the one with the second highest adaptation is the defender.

Step 2: Train and retrain.

The purpose of this step is to continuously train the attacker, through which the attacker tries to test features against the defender in order to identify the most effective features in the defender and improve the attacker's performance. Training is carried out according to Equation (5).

$$N_{\text{Train}} = \text{round}\{c.nvar\} \tag{5}$$

where c denotes the percent of selected traits; *nvar* denotes the number of all traits in a person; N_{train} denotes the number of traits that will be tested on some random traits of the defender.

Step 3: Spot an attack.

To identify the attack, SEO defines four types of attacks [33], namely Obtaining, Phishing, Diversion Theft, and Pretext. The operation at this stage involves randomly selecting one of these four attack methods. Only one parameter, the number of beta attacks, is employed as an input variable in the search process. The four attack methods are described as follows:

Obtaining:

$$def_{\mathrm{new}} = def_{\mathrm{old}} \times (1 - \sin\beta \times U(0,1)) + \frac{(\mathrm{de}f_{\mathrm{old}} + att)}{2} \times \sin\beta \times U(0,1) \tag{6}$$

Phishing:

$$\mathrm{de}\ f^1_{new} = att \times (1 - \sin\beta \times U(0,1)) + \frac{(def_{old} + att)}{2} \times \sin\beta \times U(0,1) \tag{7}$$

$$\mathrm{def}\ f^2_{new} = def_{old} \times \left(1 - \sin\left(\frac{\pi}{2} - \beta\right) \times U(0,1)\right) + \frac{(def_{old} + att)}{2} \times \sin\left(\frac{\pi}{2} - \beta\right) \times U(0,1) \tag{8}$$

Diversion theft:

$$def_{\mathrm{new}} = def_{\mathrm{old}} \times (1 - \sin\beta \times U(0,1)) + \frac{\left(def_{\mathrm{old}} + att \times U(0,1) \times \sin\left(\frac{\pi}{2} - \beta\right)\right)}{2} \times \sin\beta \times U(0,1) \tag{9}$$

Pretext:

$$\begin{aligned} \mathrm{def}\ f_{\mathrm{new}} = {} & (\mathrm{def}_{\mathrm{old}} \times \cos(\beta) \times U(0,1)) \times (1 - \sin\beta \times U(0,1)) \\ & + \tfrac{(\mathrm{def}f_{\mathrm{old}} \times U(0,1) \times \cos(\beta) + att)}{2} \times \sin\beta \times U(0,1). \end{aligned} \tag{10}$$

where $\mathrm{de}f_{new}$ denotes the new position of the defender; def_{old} and att denote the original positions of the defender and attacker; U (0, 1) denotes a uniformly distributed random number between [0, 1].

Step 4: Respond to attack.

Let *gmaxit* the number of attacks. After each attack, the new defender is evaluated and compared to the original defender. Then, the best position of the defender is selected, and if the new position of the defender is better than the attacker, the defender is swapped with the attacker, and when the attack lasts *gmaxit* times, the attack stops and a new defender has generated again. The above steps are repeated until the maximum number of iterations is reached or the algorithm stops.

Finally, the ISEO algorithm flow is described as follows:

Step 1: Input algorithm parameters: maximum number of *Imaxit* iterations, number of attacks *gmaxit*, the initial population of SCA strategy *npop*, number of sine cosine strategy iterations *ymaxit* retraining rate *c*, number of attacks β.

Step 2 Generate the initial attacker and defender according to the SCA.

Step 3: The defender is trained and retrained to generate c new solutions, and the optimal one is selected as the defender.

Step 4 Generate a new defender by randomly selecting one of the four attack methods, and replace the original defender if the new defender has better adaptation.

Step 5: Judge if the defender is better than the attacker. If so, the defender becomes the new attacker, otherwise, no change is made.

Step 6: Determine if the number of attacks reaches the upper limit. If so, stop the attacks and the algorithm proceeds to Step 7; otherwise, proceed to Step 4.

Step 7: Create a new defender.

Step 8: Determine the termination condition of the algorithm. If the maximum number of iterations *Imaxit* is reached or the preset termination conditions are met, the algorithm terminates and the attacker is output; otherwise, it proceeds to Step 3.

2.3. ISEO-BP

To address the issues of poor self-adaptation and local minima in BP neural networks, we first employ ISEO to perform global pre-optimization of the weights and thresholds of the BP neural network. We then assign the optimal weights and thresholds (i.e., attacker output) to the BP neural network as the initial weights and thresholds, and use the optimized parameters to train the BP neural network, eventually obtaining the final fault BP neural network structure for early warning.

The specific ISEO-BP processes are as follows:

1. Input neural network parameters, i.e., number of neurons in the hidden layer, activation function, number of training times, training rate, and target error to be achieved by training.
2. Input ISEO algorithm parameters, use the root mean square error of neural network prediction as the ISEO fitness function, and execute the ISEO algorithm process.
3. Train the constructed BP neural network using the weights and thresholds obtained from ISEO optimization, and obtain the BP neural network structure.
4. Input test data into the trained BP neural network to obtain output data and perform data analysis.

We have integrated the key steps of ISEO (as described in Section 2.2.2) with the main steps of the BP neural network (as outlined in Section 2.1) to provide a comprehensive overview of our proposed methodology. The resulting algorithm, known as ISEO-BP, is illustrated in the flow chart presented in Figure 3.

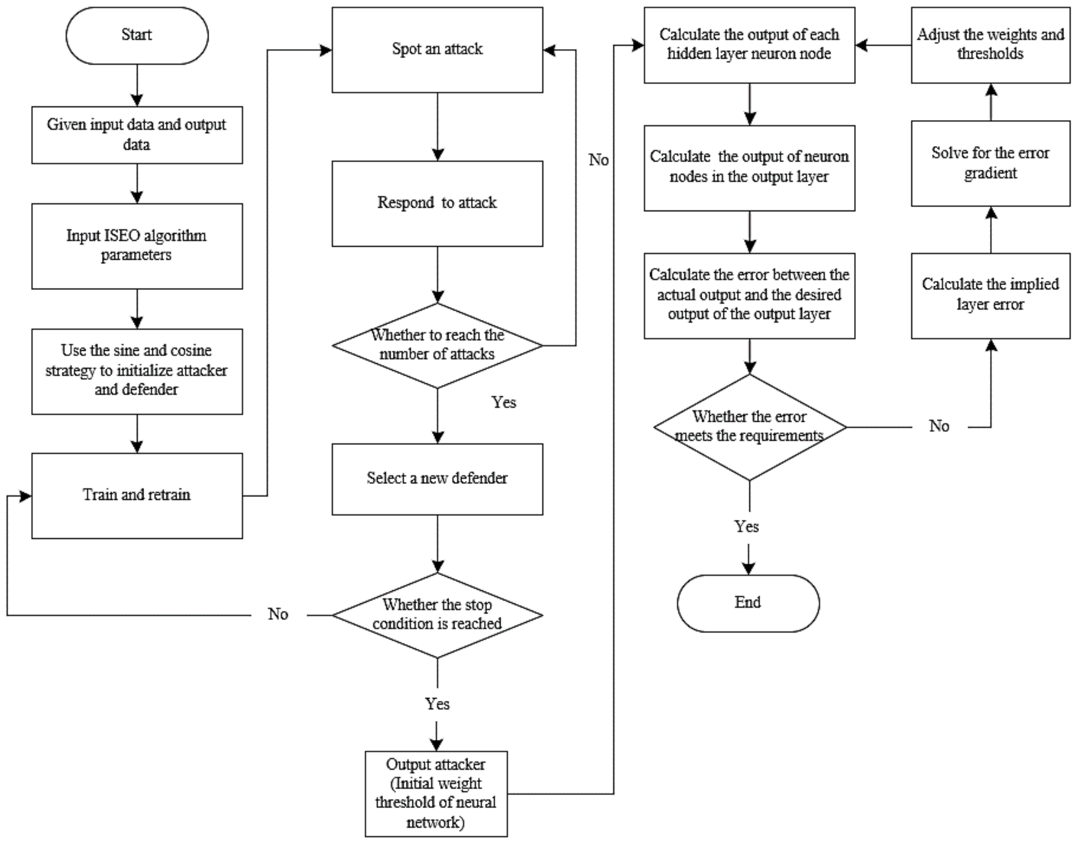

Figure 3. ISEO-BP flow chart.

As depicted in the flow chart, ISEO-BP involves several critical steps. Initially, the algorithm initializes the neural network by randomly assigning weights and biases to the neurons. Next, input data is passed through the network, generating an output via a series of weighted and nonlinear activation functions. This output is then compared to the actual label to calculate an error.

At this stage, the ISEO component comes into play, employing a positive cosine optimization strategy to generate an initial solution for the optimization process. This solution undergoes an iterative search process, which evaluates fitness values and selects new candidate solutions. The resulting solutions are subsequently fed back into the BP neural network, which uses them as weights and thresholds for starting the iteration.

The iterative process continues until either a predetermined number of iterations has been completed, or the error has been reduced to an acceptable level. Through this approach, ISEO-BP effectively combines the strengths of both the BP neural network and the ISEO algorithm, providing an efficient and effective solution for fault warning detection in hydraulic turbines and other similar equipment.

3. Case Study

Hydraulic turbines are a critical component of power equipment in generating electricity at hydropower stations, as they convert water energy into electrical energy using a hydraulic turbine as the prime mover. As water flows through the turbine, it transforms the water energy into mechanical energy, driving the rotor of the generator to produce electrical energy. The rotor of the hydraulic turbine generator is short and thick, allowing for flexibility in operation and dispatch, and requiring less time to start and connect to the grid. The rotational speed of the hydraulic turbine generator determines the frequency of the output alternating current, and to ensure the stability of this frequency, closed-loop control stabilizes the rotational speed of the prime mover. Hydraulic turbines have high utilization value in clean energy production.

Hydraulic turbines consist of several major components, including the rotor, stator, frame, thrust bearing, guide bearing, cooler, brake, and others. The stator comprises a seat, core, and winding components, and the stator core is made of cold-rolled silicon steel sheets. It can be constructed as a whole or split structure depending on manufacturing and transportation conditions. The cooling method for hydro generators typically employs closed-circulation air cooling. Very large capacity units tend to use water as the cooling medium to cool the stator directly. If both the stator and rotor are cooled simultaneously, it is called a double water intercooler hydro generator set. These components may experience various failures during turbine operation, leading to significant degradation in the turbine's performance. Due to the complex structure, it is crucial to provide advance warning of these failures and react promptly to ensure the stability of clean energy production.

To verify the effectiveness of ISEO-BP, we collected 1030 operational data points from a hydroelectric turbine in a hydropower plant, dividing all data into training and test sets at a ratio of 7:3. It is essential to note that the samples we collected are all from the turbine in healthy operation. The input data represent point data for each component under normal operation of the turbine, and the output data correspond to the data that should be output by each component during normal operation. First, we calibrated the ISEO-BP parameters (Section 3.1), then applied them to the ISEO-BP network training (Section 3.2). Finally, we carried out an ISEO-BP application analysis (Section 3.3).

3.1. ISEO-BP Parameter Calibration

In the literature, it is noted that before employing the metaheuristic algorithm and BP neural network to solve a problem, calibrating the parameters is necessary to improve the solution quality [35]. Therefore, we initially selected appropriate parameters for ISEO-BP. Based on pre-experiments and literature analysis, and considering the efficiency and quality of the algorithm, we set $Imaxit$ = 200, the number of attacks $gmaxit$ = 50, the initial population of the SAC $npop$ = 10, the number of iterations of the sine cosine strategy $ymaxit$ = 50, the maximum number of BP neural network training runs as 2000, the training error target as 0.02, and the learning rate as 0.001.

For the settings of c, β, BP neural network activation function, and the number of neurons in the hidden layer, we referred to the literature analysis and provided reference values for different levels of these five parameters, measuring them using orthogonal tests. Our given reference values are shown in Table 1. It should be noted that all codes were written in MATLAB 2018b software on an operating system using an Intel Core i7-10850H CPU @ 2.70 GHz, 2712 MHz, with 6 Cores and 12 Logical Processors.

Table 1. ISEO-BP parameter levels.

Parameters	**Alternative Reference Values**			
Levels	1	2	3	4
c	0.2	0.4	0.6	0.8
β	$\pi/9$	$4\pi/9$	$6\pi/9$	$5\pi/18$
Input layer to implicit layer functions	logsig	tansig	purelin	
Implicit layer to output layer functions	logsig	tansig	purelin	
Number of neurons in the hidden layer	10	12	14	16

As depicted in Table 1, performing all tests would result in an extensive number of trials and a significant waste of resources. Therefore, we employed Taguchi's experimental design method to form an orthogonal array for parameter calibration. According to Taguchi's test method guidance, this approach requires L16 tests. Additionally, we used the Relative Percentage Deviation (RPD) calculated with RMSE to measure algorithm performance, as shown in Equations (11) and (12). It should be noted that due to the random nature of the metaheuristic algorithm, the RPD under each parameter is averaged over 15 runs for fairness. After our measurements, the final ISEO-BP parameters are presented in Table 2.

$$RMSE = \sqrt{\frac{l}{m}\sum_{i=1}^{m}\left(y_{ac} - y_{fo}\right)^2} \tag{11}$$

where m denotes the number of output vectors; y_{ac} denotes the actual value; y_{fo} denotes the predicted value.

$$RPD = \frac{C_{RMSE} - Min_{RMSE}}{Min_{RMSE}} \tag{12}$$

where C_{RMSE} denotes the $RMSE$ of the predicted results obtained with the current parameter; Min_{RMSE} denotes the minimum $RMSE$ of all predicted results obtained with each parameter.

Table 2. ISEO-BP parameter calibration results.

Retraining rate (c).	0.6
Number of attacks (β)	$6\pi/9$
Input layer to implicit layer functions	purelin
Implicit layer to output layer functions	purelin
Number of neurons in the hidden layer	14

3.2. ISEO-BP Network Training

Using the calibrated parameters mentioned above, we trained the established algorithm model in MATLAB according to the described algorithm steps. We conducted a training simulation, and due to space limitations, some of the prediction results of ISEO-BP after one run are presented in Table 3. The results demonstrate that ISEO-BP has good data prediction accuracy and can achieve the goal of fault warning.

Table 3. ISEO-BP partial prediction results.

Actuals	Forecasts	Actuals	Forecasts	Actuals	Forecasts	Actuals	Forecasts
61.95	59.98	671.47	633.62	43.63	42.06	223.99	211.52
58.45	53.36	669.26	627.58	43.55	41.69	222.17	210.36
57.19	55.96	673.80	630.96	43.53	41.43	221.18	209.69
62.98	59.89	672.45	639.88	43.57	42.45	221.51	208.38
59.94	56.83	669.72	637.98	43.56	42.06	221.92	210.59

Based on ISEO-BP prediction data, the hydraulic turbine early warning strategy can be performed according to Equation (13).

$$|yac(i) - yfo(i)| > \varpi \quad i = 1, 2, \cdots, L \tag{13}$$

where y_{ac} denotes the true value of the hydraulic turbine operation; y_{fo} denotes the predicted value of ISEO-BP; L denotes the number of input points; ϖ denotes the artificially set fault warning criterion.

When Equation (13) is satisfied, it indicates that the equipment may be experiencing a failure. In this case, a warning notification is sent to relevant personnel, who can proceed with troubleshooting or wait for the next warning. The pseudocode for the warning strategy is illustrated in Algorithm 1.

Algorithm 1: Warning strategy

Input: Input data of the hydraulic turbine (Quantity is L), ϖ, Empty array A
Output: Whether to warn.
Obtain y_{fo} using the trained ISEO-BP
for i = 1: L
  if
    $|yac(i) - yfo(i)| > \varpi$
    A(i) = 1
  end if
end for
Issue an alert
Check the fault points according to A
Elevant personnel to check immediately or wait for the next time period to check
PS: The time period is set to ten minutes

Likewise, the fault warning strategy developed for hydraulic turbines can be adapted for other devices. The trained network can be used to output point data, and when the output data deviates from the value set by the decision maker, a fault warning determination can be triggered.

3.3. ISEO-BP Application Analysis

Here, we have examined the potential application of ISEO-BP to determine its effectiveness in providing early warnings for various failure modes of hydraulic turbines. Based on our research, we have identified the nine most common failure modes that occur during hydraulic turbine operation and have the greatest impact. These failure modes are listed in Table 4.

To assess the effectiveness of the trained ISEO-BP in failure warning, we collected operational data and output data of hydraulic turbines during each of the nine identified failure modes, with 20 sets of data for each mode. A warning was considered successful if the predicted value of the turbine output data from ISEO-BP deviated from the actual value by more than ten percent. The results of the evaluation are presented in Table 5.

Table 4. Main fault types of hydraulic turbines.

Fault Models	Fault Characteristics
Stator wire rod damage (F1)	(1) Abnormal partial discharge data of generators (2) Abnormal stator winding temperature
Air leakage from cartridge valve system (F2)	(1) Abnormal oil level of governor oil tank (2) Abnormal oil pressure of governor tank
Loose stator tooth pressure plate (F3)	(1) Stator core vertical vibration data abnormal (2) Abnormal horizontal vibration data of stator core (3) Abnormal temperature of stator tooth pressure plate (4) Abnormal stator core temperature
Water guide oil basin leaking and dumping oil (F4)	(1) Abnormal oil level in water guide tank (2) Abnormal oil temperature in water guide tank (3) Abnormal temperature of water guide tile
Hydraulic turbine cavitation (F5)	(1) Abnormal water guide oscillation (2) Abnormal tailwater inlet pressure pulsation (3) Abnormal horizontal vibration of the top cover (4) Abnormal vertical vibration of the roof
Shear pin shear off (F6)	(1) Shear pin shear off alarm (2) Large water guide oscillation (3) High horizontal vibration of the top cover (4) Large vertical vibration of the top cover
Speed control system air leakage (F7)	(1) Abnormal oil level data of governor tank (2) Abnormal oil pressure data of governor tank
Excitation system overload (F8)	(1) Abnormal excitation variable temperature data (2) Abnormal excitation current data
Rotor grounding (F9)	(1) Abnormal excitation current (2) Abnormal horizontal vibration of the stator core (3) Abnormal high vertical vibration of stator core (4) Abnormal excitation voltage

Table 5. ISEO-BP fault warning test results.

Fault Modes	Early Warning Accuracy Rate
F1	19/20 (95%)
F2	17/20 (85%)
F3	18/20 (90%)
F4	16/20 (80%)
F5	18/20 (90%)
F6	14/20 (70%)
F7	17/20 (85%)
F8	14/20 (70%)
F9	17/20 (85%)

Upon conducting the test, we observed that ISEO-BP exhibited the highest accuracy in warning about Stator wire rod damage (F1) among the nine fault types analyzed, achieving an accuracy rate of 95%. Furthermore, the warning success rate for four fault types—namely, Air leakage from cartridge valve system (F2), Loose stator tooth pressure plate (F3), Hydraulic turbine cavitation (F5), and Speed control system air leakage (F7)—was 85% or higher, falling within the reliable range. However, the warning success rate for Shear pin shear off (F6), Water guide oil basin leaking and dumping oil (F4), and Excitation system overload (F8) was low.

The setting of the early warning threshold may have some impact on the algorithm's effectiveness. Therefore, we conducted more extensive experiments, adjusting the thresholds to 5%, 10%, and 15% to test the sensitivity of ISEO-BP. The final results are displayed in Table 6.

Table 6. IEO-BP sensitivity analysis.

Fault Modes	Early Warning Accuracy Rate (5%)	Early Warning Accuracy Rate (10%)	Early Warning Accuracy Rate (15%)
F1	19/20 (95%)	19/20 (95%)	18/20 (90%)
F2	19/20 (95%)	17/20 (85%)	17/20 (85%)
F3	18/20 (90%)	18/20 (90%)	18/20 (90%)
F4	17/20 (85%)	16/20 (80%)	16/20 (80%)
F5	18/20 (90%)	18/20 (90%)	17/20 (85%)
F6	17/20 (85%)	14/20 (70%)	14/20 (70%)
F7	19/20 (95%)	17/20 (85%)	17/20(85%)
F8	16/20 (80%)	14/20 (70%)	14/20(70%)
F9	18/20 (90%)	17/20 (85%)	17/20 (85%)

According to the results in Table 6, we can observe that as the warning threshold decreases, most of the fault recognition rates increase. The accuracy of F4 and F6, which performed poorly in the previous round of experiments, has also reached 80%. However, as the warning threshold increases, the fault recognition rate of some patterns, such as F1 and F5, decreases due to the sensitivity of data point changes. It is worth noting that although the recognition accuracy may improve as the warning threshold becomes smaller, this may lead to false recognition. In practical applications, decision-makers need to consider the threshold setting holistically.

4. ISEO-BP Performance Analysis

Here, we analyze ISEO-BP's performance. First, we analyze the improvement effect of our introduced SCA strategy on the algorithm (Section 4.1) and then compare it with other advanced methods to demonstrate the high performance of our proposed ISEO-BP (Section 4.2).

4.1. SCA Effectiveness

To demonstrate the effectiveness of the SCA we introduced, we compared the RMSE of neural network predictions after ISEO and SEO optimization. To compare across the board, we set *gmaxit* to 30, 40, and 50 and *Imaxit* to 200, 300,500, and the only difference between ISEO and SEO is that SCA is not integrated into SEO. The average final results after 15 runs are shown in Table 7.

Table 7. SCA effectiveness comparison results.

Algorithm Parameters	SEO-BP		ISEO-BP	
gmaxit, *Imaxit*	*RMSE*	Number of First Convergence	*RMSE*	Number of First Convergence
30,200	75.36	121.68	73.48	110.36
30,500	73.28	308.56	72.52	288.56
40,200	74.68	122.37	73.98	109.32
40,500	72.93	262.56	71.62	248.63
50,200	72.28	113.28	70.96	103.06
50,500	71.86	296.89	70.16	272.59

Based on the results presented in Table 7, we can observe that the prediction results of ISEO-BP outperform those of SEO-BP under different parameter combinations. The RMSE values for ISEO-BP are smaller than those of SEO-BP, and the convergence times for ISEO-BP are also better than those for SEO-BP. These observations reflect the strong performance of ISEO-BP and further illustrate the effectiveness of the positive cosine optimization strategy introduced in this paper.

4.2. Comparison with Other Methods

To further evaluate the performance of the proposed ISEO-BP, we employed XGBoost [36], IBA-BP [37], GA-BP [38], PSO-BP [39], and multi-feature sparrow search algorithm optimized support vector machine algorithm (MSSA-SVM) [40] to solve the aforementioned cases, comparing their performance using two metrics: *RMSE* and R^2. For a detailed description of these metrics, interested readers can refer to the literature [41]. Additionally, we present a comparison of the solution efficiency for each algorithm to illustrate the effectiveness of ISEO-BP from multiple perspectives. It should be noted that the algorithms used for the above comparison are based on the literature, and other parameters remain the same as in the previous section. To ensure fairness, we also ran each algorithm 15 times to compare the evaluation results. Table 8 displays the average results after these 15 runs, while Figure 4 shows the statistical results of the 15 runs.

Table 8. Performance comparison results of different algorithms.

Algorithms	*RMSE*	R^2	*CPU/s*
XGBoost	72.92	97.85	22.78
IBA-BP	71.85	98.35	21.91
GA-BP	72.56	98.12	22.56
ISEO-BP	**70.71**	**98.97**	21.64
PSO-BP	70.89	98.68	22.02
MSSA-SVM	71.53	98.55	**21.60**

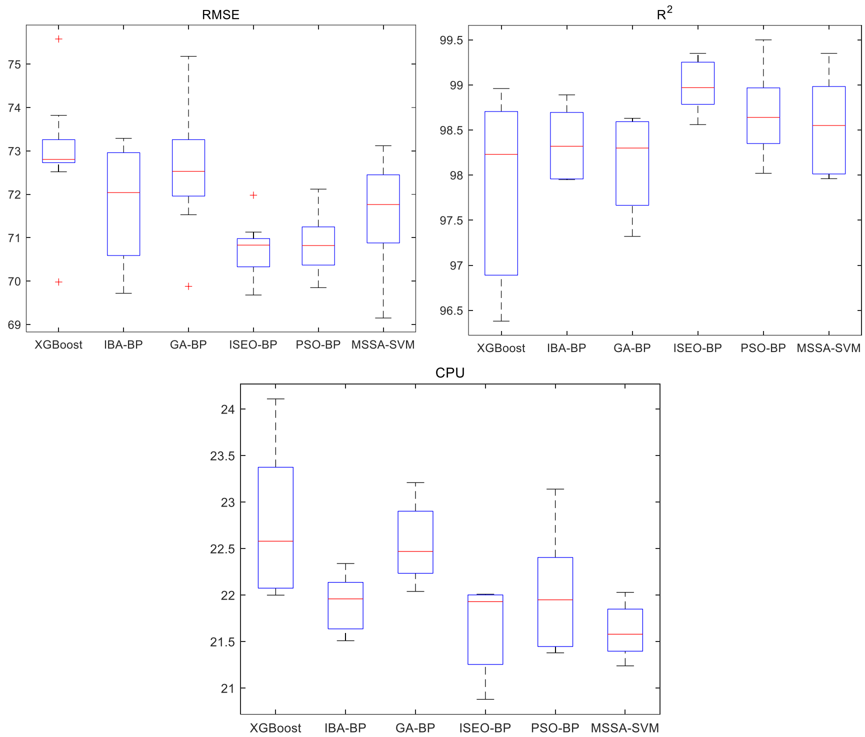

Figure 4. Box plot of algorithm performance comparison results (+represents outliers).

In addition, we tested the six algorithms for fault warning using the method in Section 3.2, the final results are shown in Table 9. Table 9 displays the average results for the three different thresholds.

Table 9. Fault warning test results.

Algorithms	Early Warning Accuracy Rate (%)
XGBoost	76
IBA-BP	80
GA-BP	82
ISEO-BP	88
PSO-BP	85
MSSA-SVM	79

According to the results presented in Table 8, our proposed IEO-BP attains optimal values for *RMSE* and R^2. Meanwhile, MSSA-SVM achieves the best *CPU* time, with IEO-BP taking second place in this metric. However, the increase in *CPU* time corresponds to an improvement in accuracy. The statistical analysis reveals that IEO-BP is stable across all three indices, further highlighting its superiority.

In addition, based on the fault test results in Table 9, IEO-BP's early warning efficacy surpasses other advanced methods. Overall, IEO-BP demonstrates exceptional performance in this study.

5. Conclusions and Future Work

The hydraulic turbine is a crucial component for ensuring the seamless operation of the entire hydroelectric power plant chain and maintaining its reasonable and stable functioning. Providing accurate fault warnings for it is of great importance to enhance operational efficiency. In this paper, we introduce a fault warning method called ISEO-BP to improve the hydraulic turbine fault warning level. First, we enhanced the SEO using the positive cosine strategy, effectively addressing its existing limitations. Then, we optimized the BP neural network with ISEO and proposed our fault warning strategy. Experimental results indicate that our proposed ISEO-BP achieves higher prediction accuracy compared to other methods. ISEO-BP attained optimal values for all three performance metrics: *RMSE*, R^2, and *CPU* time, as illustrated in Table 8. Moreover, the fault warning effect test (Table 9) revealed that ISEO-BP improved accuracy is higher. This enhancement can effectively accomplish the purpose of fault warning and foster the high-quality development of the entire hydropower plant operation.

However, while our paper presents an effective solution to the hydraulic turbine fault warning challenge, there remains room for further exploration. Future researchers can suggest more efficient fault warning strategies to optimize SEO using adaptive optimization approaches and local search operators [30,31], combine SEO with other heuristics [32–34], and develop more reasonable and effective BP neural network activation functions [35–37] to further increase efficiency. Addressing uncertainty and ambiguity is essential in real-world applications; one way to tackle this issue is by extending neural networks to fuzzy neural networks [38–40]. Fuzzy logic can manage fuzzy or uncertain inputs, allowing neural networks to better handle uncertainty and ambiguity in the real world [42–44]. Investigating the use of neural networks to learn and establish a mapping relationship between inputs and outputs, and then employing this mapping relationship in a fuzzy control system to achieve control of fuzzy variables, would be an interesting avenue to explore [45–49].

In conclusion, we encourage researchers to expand the ISEO-BP presented in this paper by applying the proposed warning strategy to more devices [50–52]. This will contribute to further enhancing the accuracy and efficiency of hydraulic turbine fault warnings and promoting the development of the entire hydropower plant operation.

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