Human Error Evaluation Model of Civil Aviation Maintenance Based on Grey Wolf Optimizer

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Abstract. Today, with the rapid development of science and technology, human error has already surpassed mechanical failure and become the most important factor in safety accidents. In order to reduce the occurrence of human error in civil aviation maintenance, and to improve the quality of maintenance production, four levels and 18 factors affecting human error in civil aviation maintenance are proposed in this paper, Taking Hongqiao base of Eastern Airlines as an example, a questionnaire survey was used to collect data, and an Inertial Adaptive Hybrid Gray Wolf Optimization (IAHGWO) was proposed, which combined with particle swarm optimization (PSO) and three improved strategies, and an evaluation model was constructed to use IAHGWO to train BP neural network. The results show that the evaluation model has good practicability and accuracy.

1. Introduction

These Human error are term widely mentioned in civil aviation safety. It refers to the behavior that people fail to complete the specified task according to the established plan, resulting in the loss of equipment and property. With the progress of science and technology, human error has already surpassed mechanical failure and become the most important factor in civil aviation maintenance accidents.

This paper designs a human error evaluation model based on deep learning, which is helpful to strengthen the internal control of human error of maintenance personnel in civil aviation enterprises, and it reduced the incidence of human error in maintenance, improved the quality of safe production. At the same time, it makes up for the defects of real-time, predictability and pertinence in the control of individual human error of maintenance personnel in civil aviation enterprises at the present stage.

The core of the deep learning optimizer of the system is to build an evaluation model based on BP neural network by analyzing the inducement of human error. The weights and thresholds of the BP neural network trained by the inertial adaptive Grey Wolf Optimizer are presented for the first time. So that the system has good practicability and accuracy[1-2].
2. Model construction

2.1. Input/output layer design

The impact factors (input layer) of the evaluation system are studied through the classical literature of human error: SHEL model, Reason model, Murphy's theorem, and HFACS system[3], combined with the business characteristics of the enterprise (Hongqiao Maintenance Base of China Eastern Airlines as an example) and based on the Management of Maintenance Errors for Aviation Personnel, 18 factors affecting human error are put forward at various levels: self level (M1-M4), environment level (N1-N4), organization level (X1-X4), and management level (Y1-Y6)[4-5].

| Factors affecting | Factors affecting | Factors affecting |
|-------------------|-------------------|-------------------|
| M1 health N3      | Supply chain      | Y1 The structure  |
| M2 Degree of confidence N4 | Life safeguard | Y2 System of rules and regulations |
| M3 Pressure of work X1 | Interpersonal relationships | Y3 Performance management |
| M4 Professional skill X2 | Team collaboration | Y4 Quality supervision |
| N1 Tooling equipment X3 | Responsibility assignment | Y5 Education and training |
| N2 Natural environment X4 | The human resources | Y6 The enterprise culture |

The evaluation level of the system (output level) mainly refers to the "Management Measures for Safety Credits of Maintenance Personnel" of China Eastern Airlines. The safety credits take a natural year as a period, a total of 10 points. In case of general maintenance error/serious maintenance error/maintenance accident symptoms, according to the seriousness of the circumstances, the safety points will be deducted from 1-3 points / 3-7 points / 7-10 points; Visited 4 experts from the quality department of China Eastern Airlines Hongqiao Maintenance Base, as well as a large number of on-duty maintenance personnel, and finally determined as follows: the existing safety score of 3 (including) is defined as unsafe, it is "High possibility human error"; The existing safety score 7 points (inclusive) is defined as general, that is "Mid possibility Human error"; The existing safety score above 7 points is defined as safe, it is "Low possibility human error".

2.2. Optimizer Design

2.2.1. The Back Propagation Neural Network

BP neural network is a typical error back propagation Optimizer. From the structure is divided into input layer, hidden layer, output layer. Each layer is composed of many simple structures of neuron units. They can perform parallel computations at the same time as other units give them input. The commonly used nonlinear transfer function is S-type function. The training process is to calculate the error of the output leading layer through the error between the output and the expectation, and reverse through each intermediate layer, calculate and revise the weight between each connection one by one, and finally return to the input layer. The memory training will not be stopped until the output layer error is less than the target value. BP neural network has excellent nonlinear mapping ability and flexible network
structure. A 3-layer BP neural network can represent arbitrary nonlinear functions. It is a common Optimizer to solve nonlinear fuzzy classification problems.

2.2.2. Grey Wolf Optimizer (GWO)
The Wolf Optimizer[6] It is an intelligent Optimizer based on animal behavior. It builds mathematical models by imitating the social relationships of wolves, as well as their hunting and hunting behaviors. The Wolf pack is divided into four levels, each of which has a strict division of labor: the alpha Wolf is the leader of the pack and the supreme Wolf, who has absolute leadership over the wolves and must obey every other Wolf. The alpha Wolf is the second Wolf to the alpha Wolf, and he only takes orders from the alpha Wolf and helps lead the other wolves. The alpha wolves, once again, obey the leaders of the alpha and beta wolves, and can lead only normal wolves.

- Hunting behavior:
  \[
  \vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)|
  \]
  \[
  \vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D}
  \]
  \[
  \vec{A} = 2a \cdot \vec{r}_2 - a
  \]
  \[
  \vec{C} = 2\vec{r}_1
  \]
  \[
  a = 2 - 2 \left( \frac{t}{\text{max}} \right)
  \]

  \[
  \vec{D}: \text{The distance between the individual and the food; } \text{”t” represents the number of current iterations; } \vec{C}: \text{The vector is the perturbation to the prey; } \vec{X}_p, \text{ Represents the position of the target; } \vec{X} \text{ is the current position of the individual. In the iterative process of the Optimizer, the convergence factor a decreases linearly from 2 to 0, and } \vec{r}_1, \vec{r}_2 \text{ is a random vector in [0,1].}
  \]

- Searching behavior:
  \[
  \vec{D}_a = |\vec{C} \cdot \vec{X}_a(t) - \vec{X}(t)|
  \]
  \[
  \vec{D}_b = |\vec{C} \cdot \vec{X}_b(t) - \vec{X}(t)|
  \]
  \[
  \vec{D}_\omega = |\vec{C} \cdot \vec{X}_\omega(t) - \vec{X}(t)|
  \]

  In the formula (2), \(\vec{X}_1, \vec{X}_2, \vec{X}_3\) represent the position vectors of alpha, beta, omega in the current population, respectively. \(\vec{X}\) represents the position vector of the gray Wolf; \(\vec{D}_a, \vec{D}_b, \vec{D}_\omega\) represent the distance between the current candidate gray Wolf and the optimal three wolves respectively; \(|\vec{A}| > 1\), the wolves scattered among themselves as much as possible and searched for prey. \(|\vec{A}| < 1\), gray wolves will gather to search for prey in one or more areas.

  \[
  \vec{X}_1 = \vec{X}_a - \vec{A}_1 \cdot \vec{D}_a
  \]
  \[
  \vec{X}_2 = \vec{X}_b - \vec{A}_2 \cdot \vec{D}_b
  \]
  \[
  \vec{X}_3 = \vec{X}_\omega - \vec{A}_3 \cdot \vec{D}_\omega
  \]

  Formula (3) defines the step size and direction of an individual in the \(\omega\) Wolf pack toward alpha, beta, and alpha, respectively, and Formula (4) defines the final position of the \(\omega\) Wolf.

  \[
  \vec{X}_{(t+1)} = \frac{1}{3}(\vec{X}_1 + \vec{X}_2 + \vec{X}_3)
  \]
2.2.3. Particle Swarm Optimization (PSO)

Particle swarm optimization[7] is inspired by the migration and gathering behavior of birds in foraging. In the initial state, PSO is a group of random particles, which are affected by individual extremum and global extremum in the iteration process, so that the particles approach and fall to the optimal solution in space. The core formula is as follows (5):

\[
v_i = \omega \cdot v_i + c_1 \cdot r_1 (p_{best_i} - x_i) + c_2 \cdot r_2 (g_{best} - x_i) \quad x_i = x_i + v_i
\]  

\[(5)\]

I = 1, 2, ..., N, N is the total number of particles; \(v_i\) is the particle velocity, \(r_1, r_2\) is the random number \([0,1] ; c_1, c_2\): the learning rate is a constant; \(\omega\) is the inertial factor, which is a non-negative number.

2.3. Optimizer Optimization

- Social information sharing mechanism

Inspired by particle swarm optimization To make the updating position of \(\omega\)-wolves be influenced by the global optimal solution, and to establish an information sharing and communication mechanism for the entire Wolf pack.

\[
v_{i+1} = \omega_{i+1} \cdot x_i + c_1 r_1 (p_{best_i} - x_i) + c_2 r_2 (g_{best} - x_i)
\]

\[
x_{i+1} = x_i + v_{i+1}
\]  

\[(6)\]

- Adaptive inertia factor strategy

According to Equation (5), the size of inertia factor \(\omega\) directly affects the development performance of the particle swarm optimization Optimizer. The literature, It has been proved that the adaptive variation of \(\omega\) in the range of \([0.4,0.9]\) effectively improves the particle swarm optimization Optimizer. Combined with the basic principle of gray Wolf Optimizer [8], put forward the average step size of \(\omega\) wolf, and transform Equation (4) into

\[
\overline{X} = \sum \frac{X_{i+1}}{i}
\]

\[(7)\]

\[
\omega_{i+1} = \omega_{start} \cdot \left( \frac{\omega_{end}}{\omega_{start}} \right) \frac{\overline{X}_{i+1}}{\overline{X}_i - \overline{X}_i} \cdot \frac{t}{t_{MAX}}
\]

In Equation (6) above, \(\omega_{start}\) is the initial value and \(\omega_{end}\) is final value of \(\omega\), and \(t_{MAX}\) is the maximum iteration number.

- Fixed perturbation strategy \(\tilde{C}\)

The standard gray Wolf Optimizer is the perturbation of the Wolf group to the target, \(\tilde{C}\) which is a random value of \([0,2]\). Several variables were introduced into the above strategy. May cause system instability. So the fixed value strategy is used to stabilize the system optimization. \(\tilde{C}\) After repeated trials \(\tilde{C} = 1.9\)

In summary, the steps of IAHGWO Optimizer to train BP neural network are as follows:
2.4. Comparative Simulation

The simulation comparison experiment was constructed by Matlab2018A, the representative reference function Table 2, was selected from the classification of 23 reference function tables used in the original text of the grey Wolf Optimizer for comparison. Set the total number of wolves to 30. The number of iterations is 500, and the average value of 30 simulations is taken. The result is shown in Figure 2 below. Through comparison, it can be clearly seen that the performance of the inertial adaptive mixed gray Wolf Optimizer (IAHGWO) proposed in this paper is significantly better than that of the standard gray Wolf Optimizer. The fitness function of the inertial adaptive mixed gray Wolf Optimizer is set as:

$$\text{fitness} = \arg \min \left\{ \sum_{i=1}^{N} (\text{Simout} - \text{GroundTruth})^2 \right\}$$

The error value of BP neural network after optimization is shown in Figure 3., which shows a trend of continuous decline, indicating that IAHGWO has played an optimization role in BP neural network. The accuracy of BP neural network increased from 87.65% to 95.88%.

Table 2. Reference function parameter

| Expression          | Dimension | Range      |
|---------------------|-----------|------------|
| $f_i(x) = \sum_i x_i \cdot x_i$ | 30        | $x \in [-10,10]^n$ |
\[ f_i(x) = \sum \sum x_j^2, \]
\[ f_i(x) = \sum \left[ 100(x_{i1} - x_j)^2 + (x_{i2} - 1)^2 \right] \]
\[ f_i(x) = \sum \left[ x_i^2 - 10 \cos(2 \pi x_i) + 10 \right] \]
\[ f_i(x) = -20 \exp \left[-0.5 \sum_{j=1}^{n} x_j^2 \right] - \exp \left[ \frac{1}{n} \sum_{i=1}^{n} \cos(2 \pi x_i) \right] + 20 + x \]
\[ f_i(x) = 0.1 \left[ \sin^2(5x_1) + \sum (x_i - 1)^2 \right] + \sin^2(\sum (x_i - 1)) + \frac{\sum (x_i - 5,100,4)^2}{100} \]
\[ f_i(x) = \sum_{j=1}^{n} \frac{1}{100} \left[ \sum_{j=1}^{n} (x_i - x_j)^2 \right] \]
\[ f_i(x) = \frac{1}{4} \left( \sum_{j=1}^{n} \frac{1}{n} \sum_{i=1}^{n} (x_i - x_j)^2 \right) \]

Figure 2. Performance comparison between IAHGWO and standard GWO
3. Data collection and analysis
In terms of data collection, this paper takes the Hongqiao Maintenance Base of China Eastern Airlines as an example. 200 questionnaires were sent out and 173 were collected, among which 157 were effective, and the effective recovery rate was 78%. The working age of the subjects was between 2 and 20 years and they were engaged in front-line maintenance work. The reliability and validity of the
collected data were analyzed by SPSS22. The reliability and validity evaluation coefficients in Table 3 indicated that the above-mentioned data collected by the questionnaire could be adopted.

| The reliability | Cronbach’s α | 2 | A number of |
|-----------------|--------------|---|------------|
| validity        | KMO          | Bartlett’s Sphericityχ² | Sig |
|                 | 0.93         | 2473.241                | 0   |

4. Model Application
Matlab2018a was used to substitute the collected data into the standard BP neural network for training, and Figure 4 was obtained. It can be seen that the error of BP neural network converged at the 251st step. It shows that the BP neural network model has a good nonlinear relationship with human error in civil aviation maintenance.

The IAHGWO-BP model is used to calculate the value which is almost similar to the expected value and is consistent with the actual situation of the two people. It can be said that this model has quite strong practicability.

5. Conclusion
The inertial adaptive hybrid gray Wolf Optimizer (IAHGWO) is proposed innovatively. By comparing with the standard gray Wolf Optimizer, the superiority of this Optimizer is proved.

The error of BP neural network was significantly reduced by using the inertial adaptive hybrid gray Wolf Optimizer (IAHGWO), and the accuracy of BP neural network was improved from 87.65% to 95.88%.

Taking Hongqiao Maintenance Base of China Eastern Airlines as an example, it is verified that the human error evaluation model has good practicability and accuracy, and it will be popularized well in the future.

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