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Health Condition Evaluation for a Shearer through the Integration of a Fuzzy Neural Network and Improved Particle Swarm Optimization Algorithm

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Abstract: In order to accurately evaluate the health condition of a shearer, a hybrid prediction method was proposed based on the integration of a fuzzy neural network (FNN) and improved particle swarm optimization (IPSO). The parameters of FNN were optimized by the use of PSO, which was coupled with a premature judgment and mutation mechanism to increase the convergence speed and enhance the generalization ability. The key technologies are elaborated and the flowchart of the proposed approach was designed. Furthermore, an experiment example was carried out and the comparison results indicated that the proposed approach was feasible and outperforms others. Finally, a field application example in coal mining face was demonstrated to specify the effect of the proposed system.

Keywords: shearer health condition evaluation; fuzzy neural network; particle swarm optimization

1. Introduction

As a kind of important mechanized mining equipment, a shearer is usually used to cut and load coal in modern fruitful and efficient coal mining, which directly impacts on the automation level of the entire mechanized mining face [1–3]. The reliability of a shearer decides whether the coal can be mined with high efficiency and low risk. Therefore, effective and accurate evaluation of the health condition of a shearer is an important way to reduce safety accidents and enhance coal mine production, and it has become a challenging and significant research subject.

Due to the poor working conditions of coal mining, it is rather difficult to acquire the health condition of a shearer depending only on the subjective consciousness of an operator. In the real mining condition, some key index parameters are very important and have a strong relationship with the shearer health condition. However, the relationship is highly nonlinear in nature so that it is hard to develop a comprehensive mathematic model. To deal with this kind of problem, the commonly used methods are fuzzy theory and neural networks [4–6]. A fuzzy neural network (FNN) is the combination of fuzzy logic and a neural network, and possesses the advantages of processing vague information and good learning abilities. It can also handle imprecise information through linguistic expressions. For several decades, FNN has attracted much attention and has been applied in many domains [7,8].

However, the parameters of FNN have great influences on its performance. The common learning algorithm for FNN is the gradient descent method (GD), which may lead to being easy to trap into

a local minimum point and poor ability on a global search [9,10]. In addition, the performance of GD training a FNN depends on the initial settings for system parameters, and the method has to derive and formulate different mathematical expressions to adapt the corresponding networks topologies. Based on the past works on artificial intelligent optimization algorithms, this paper tries to tackle this problem.

Through the survey mentioned above, we propose an integrated approach based on a fuzzy neural network and improved particle swarm optimization (IPSO) to solve the problem of shearer health condition evaluation. The remainder of this paper is as follows: Section 2 reviews some related works based on the literature. The improved fuzzy neural network model is proposed in Section 3. The experiment example is provided to verify the proposed method in Section 4. In Section 5, a field application example is presented to indicate the actual application effect of proposed model in predicting the shearer health condition. Our conclusions and future work are summarized in Section 6.

2. Literature Review

In this section, we will review some recent publications, which mainly contain two research focuses: shearer health condition and fuzzy neural networks. Furthermore, we offer a discussion about the relevant literature.

2.1. Relevant Studies on Shearer Health Condition

Currently, some scholars have made some related research around shearer health condition. In [11], an improved neural network model was proposed based on the integration of quantum calculations and neural networks to monitor the working states of the large mining rotating machines. In [12], a fuzzy inference system was proposed to provide a correct and timely diagnosis mechanism of the shearer health condition. In [13], a shearer fault diagnosis algorithm based on a fuzzy decision tree was proposed to enhance the accuracy and efficiency of shearer fault diagnosis by analyzing the experiment. In [14], a fault diagnosis method based on the two-scale decomposition and reconstruction in wavelet analysis was proposed for the failure of mechanical systems on shearers. In [15], Niu *et al.* put forward the OPC technology into a shearer monitoring system to efficiently monitor the condition of the shearer working state parameters and improve the level of automation of the shearer industry.

2.2. Relevant Improvements for Fuzzy Neural Network

In [16], a wavelet Petri fuzzy neural network was proposed based on the integration of a wavelet fuzzy neural network and Petri net to improve the transient and steady-state responses of the squirrel-cage induction generator system at different operating conditions. The study in [17] modified the fuzzy neural network with a max-min algorithm to perform the supervised classification of data. In [18], a fuzzy wavelet network was constructed and initialized by the kernel method and wavelet multi-resolution analysis. In [19], Liu *et al.* proposed a recurrent self-evolving fuzzy neural network that employed an on-line gradient descent learning rule to address the electroencephalography regression problem in brain dynamics for driving fatigue. In [20], the rough sets theory was coupled with a fuzzy artificial neural network to improve the learning process. In [21], a fuzzy differential evolution learning method was used for an interactively recurrent functional neural fuzzy network to solve the control and the prediction problems. The study in [22] presented a systematic approach for off-season longan forecasting using neural network, fuzzy neural network, support vector regression, and fuzzy support vector regression. In [23], the Takagi-Sugeno-Kang-type probabilistic fuzzy neural network was presented with an asymmetric membership function to improve the control effect for a three-phase grid-connected PV system.

2.3. Discussion

When focused on the literature mentioned above, there are no studies about the evaluation method for shearer health condition through its working parameters and it can be deduced that some proper

improvements are necessary for the FNN in order to obtain accurate prediction performance. Therefore, this paper proposed a prediction method for shearer health condition evaluation based on a fuzzy neural network and particle swarm optimization. A premature judgment method was introduced in PSO to evaluate when the particles were in the premature state. In addition, a mutation mechanism

based on resetting the velocity was proposed to enable particles to possess a new momentum and jump out of the partial optimization space. Then, the improved PSO was programmed and used to optimize the parameters of the FNN. The experiment example and field application were carried out and the proposed approach was proved feasible and outperformed others.

3. The Proposed Approach

3.1. Fuzzy Neural Network (FNN)

In this paper, a FNN with four layers is employed and the architecture of the four-layer FNN is shown in Figure 1.



Figure 1. The architecture of a four-layer fuzzy neural network.

In the first layer, the output of each node can be calculated as follows:

$$\mu_{ij} = \exp\left[-(x_i - c_{ij})^2 / \sigma_{ij}^2\right] \tag{1}$$

where i = 1:k, j = 1:n, x_i , μ_{ij} , c_{ij} , and σ_{ij} are the inputs of FNN, membership function, center (mean), and width (variance) of the membership function of the *j*th fuzzy set of the *i*th input variable x_i , respectively. k is the dimension of input vector and n is the number of fuzzy sets, which can be interpreted as the number of neurons in the hidden layer.

In the second layer, the output of each node is labeled as Π , which can be obtained through the product of all input signals for each node, described as follows:

$$z_j = \prod_{i=1}^k \mu_{ij} = \mu_{1j}(x_1) \times \mu_{2j}(x_2) \times \dots \times \mu_{kj}(x_i)$$

$$(2)$$

In the third layer, two parameters of *a* and *b* can be calculated as follows:

$$a = \sum_{j=1}^{n} \omega_j z_j$$

$$b = \sum_{j=1}^{n} z_j$$
(3)

where ω_j is the connection weight between the second layer and third layer. Eventually, the overall output of FNN can be represented by y = a/b.

In thee FNN, three kinds of parameters, including center (c_{ij}), width (σ_{ij}), and connection weight (ω_j), have a significant impact on its performance. The training of these parameters has a great influence on the performance of the FNN. For the $k \times n$ means and variances of the membership layer (c_{ij} and σ_{ij} , i = 1:k, j = 1:n), and the n weights of the output layer (ω_j , j = 1:n), there are 2kn + n parameters of the four-layer FNN. In order to express conveniently, a state vector X(t) consisting of the parameters at a given time step t can be given as follows:

$$X(t) = [c_{11}, \cdots, c_{1n}, \cdots, c_{k1}, \cdots, c_{kn}, \sigma_{11}, \cdots, \sigma_{1n}, \cdots, \sigma_{k1}, \cdots, \sigma_{kn}, \omega_1, \omega_2, \cdots, \omega_n]$$
(4)

In this work, an evolutionary algorithm, namely, a particle swarm optimization algorithm (PSO), is employed to adaptively adjust these parameters. The PSO treats the parameters of the FNN as a particle and many particles can generate a swarm to find the optimal parameters. Then, the particle swarm is updated by guiding the current swarm toward the best overall particle. The specific steps can be described in the following parts.

3.2. Improved Particle Swarm Optimization Algorithm

In the PSO, each group of parameters of the FNN can be regarded as a "particle" in the search space. The swarm including *M* particles forms a D (D = 2kn + n) dimensional search space and the parameter values can be represented by the position of a particle. The position of the *i*th particle is marked as $X_i = (X_{i1}, X_{i2}, \dots, X_{iD})$ to express Equation (4), and the corresponding velocity is marked as $V_i = (V_{i1}, V_{i2}, \dots, V_{iD})$, which includes a direction and distance, determining the search capability of each particle in the space. The fitness of particles can be evaluated through the following error function:

$$F = \frac{1}{q} \sum_{i=1}^{q} (yd_i - y_i)^2$$
(5)

where *q* is the number of training samples, y_i denotes the network output of the *i*th sample; and yd_i denotes the desired output of the *i*th sample.

The individual extremum is $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})^T$ and the global extremum of the particle swarm is $P_g = (P_{g1}, P_{g2}, \dots, P_{gD})^T$. The updated equations for the velocity and position are as follows:

$$V_{ij}^{t+1} = \alpha v_{ij}^t + c_1 r_1 (p_{ij} - X_{ij}^t) + c_2 r_2 (p_{gj} - X_{ij}^t)$$
(6)

$$X_{ij}^{t+1} = X_{ij}^t + V_{ij}^{t+1}$$
(7)

where i = 1:M, j = 1:D, α denotes inertia weight. t denotes the current number of iterations, c_1 and c_2 , called the learning factors, can be set to 1.5 and 2.5, respectively, and r_1 and r_2 are the random numbers in the range [0,1]. In this paper, the inertia weight is updated nonlinearly through the following equation, which is neither constant nor linear gradient, but diminishes non-linearly with the increase of the number of iterations:

$$\alpha = (\alpha_{\max} - \alpha_{\min}) \times \left(\frac{t_{\max} - t}{t_{\max}}\right) + \alpha_{\min}$$
(8)

where α_{max} and α_{min} represent the maximum and minimum inertial weight, respectively, and can be set to 0.9 and 0.4; t_{max} is the maximum number of iterations.

However, PSO often suffers from the problems of slow convergence speed and premature convergence because of the quick loss of diversity in the later period [24,25]. In this paper, a premature judgment and mutation mechanism is proposed to improve the PSO, abbreviated as IPSO.

The position of particles is composed of the parameters of the FNN and can determine the fitness of the particle, so we can evaluate the performance of the particle swarm by the overall changing of all particles fitness. The group fitness variance δ^2 is employed to judge the premature level of particles, which can be defined as follows:

$$\delta^2 = \frac{1}{M} \sum_{i=1}^{M} \left(\frac{F_i - F_{avg}}{F} \right)^2 \tag{9}$$

where F_i denotes the fitness of the *i*th particle, F_{avg} is the average fitness of all particles, F denotes the normalization factor, which can be determined as follows:

$$F = \max\left\{1, \max\left\{|F_i - F_{avg}|\right\}_{i=1}^{M}\right\}$$
(10)

When δ^2 is smaller than a specified value *H* (*H* is a predetermined constant beforehand), the algorithm is considered as falling into premature. Hence, to avoid this drawback of PSO, a mutation mechanism based on resetting the velocity is proposed to enable particles to possess a new momentum according to the following equation:

$$V_{ij}^{t} = V_{\min} + (V_{\max} - V_{\min})V_{ij}^{t}$$
(11)

where $[V_{\min}, V_{\max}]$ is the velocity range of the particles. Proper velocity range can ensure that the performance of the algorithm.

3.3. Optimizing the Parameters of FNN with IPSO

By the use of the improved evolution algorithm, the three kinds of FNN parameters (c, σ , and ω) can be determined. In the process of searching optimal parameters, the vector described as Equation (4), is represented by a particle. The objective of training FNN is to improve the prediction performance of FNN model and the fitness function has been formulated as Equation (5). The process of optimizing the FNN parameters by IPSO can be described as follows.

- Step 1 Initialize the particle swarm size M, the maximum of generations t_{max} , the maximum inertial weight α_{max} , the minimum inertial weight α_{min} , c_1 and c_2 , r_1 and r_2 , $[V_{min}, V_{max}]$, the number of input variables k, the number of neurons in the hidden layer n, H, and set D = 2kn + n, t = 1;
- Step 2 Update the velocity V_i and position X_i of each particle according to Equations (6) and (7), respectively. Synchronously, update the inertial weight α according to Equation (8);
- Step 3 The individual best P_i is compared with each particle; if P_i is worse than the fitness value of each particle, then P_i is updated as current position;
- Step 4 The global best P_g is compared with individual best P_i of each particle; if P_g is worse than P_i , then P_g is updated as current position;
- Step 5 If the convergence criteria or one of the stopping criteria (generally, a sufficiently good fitness or maximum iteration is met) is satisfied, go to step 7;
- Step 6 The group fitness variance δ^2 is calculated through Equations (9) and (10). If $\delta^2 < H$, the velocity and position of the premature particles are updated according to Equations (11) and (7), and the inertial weight α is updated according to Equation (8), go back to Step 3; otherwise, go back to Step 2. Let t = t + 1; and
- Step 7 The optimal parameters *c*, σ , and ω of the FNN model can be obtained.

According to the above description about the FNN coupled with IPSO, the proposed approach is an iterative algorithm and can be coded on the computer. The flowchart is summarized, as shown in Figure 2.



Figure 2. Optimizing the parameters of the fuzzy neural network (FNN) model with improved particle swarm optimization (IPSO).

4. Experiment and Discussion

4.1. Sample Data Preparation

According to the health analysis of the shearer, there are many variables which can be used to evaluate the shearer health condition. However, not all variables of the shearer have significant correlation to its health condition, and too many input variables to the FNN will reduce the training efficiency. Therefore, in this study, four variables of the shearer: cutting motor current (CC), traction motor current (TC), cutting part temperature (CT), and traction speed (TS), are selected for training the FNN model. The shearer health grade is the output of the forecasting model and its quantitative data can be scored according to the experts. In the experiment, we divide the health grade into four levels, from 1 to 4, and the higher the grade, the worse the shearer health condition. The notations for all of the variables are shown in Table 1. Based on above analysis, we can select samples for the FNN from the original database in the 22210 coal face of Pingdingshan Coal Industry, Henan, China.

| Notation | Variable |
|-----------------------|-------------------------------|
| x_1 | Cutting motor current (CC) |
| <i>x</i> ₂ | Traction motor current (TC) |
| <i>x</i> ₃ | Cutting part temperature (CT) |
| x_4 | Traction speed (TS) |
| y | The health grade of shearer |

Table 1. The notations of variables.

In general, the selected samples may contain some system noise. In order to specify the noise level, we had researched the problem of system noise through wavelet analysis. Taking the cutting motor current as an example, the analysis results of system noise were illustrated in Figure 3. The results indicated that the system noise fluctuated in the interval of [-0.8, 0.8] and had little impact on the subsequent application of cutting motor current. In summary, the collected datasets could be directly used as the sample data for the training and testing of proposed predictor.



Figure 3. System noise analysis of cutting motor current: (**a**) the original signal of cutting motor current; and (**b**) the system noise information.

4.2. Experiment Results

To verify the performance and effectiveness of the FNN with IPSO (abbreviated as IPSO-FNN), we randomly selected two subsets from the original dataset, and each subset was composed of 5000 samples. One was treated as the training set and another was treated as the testing set. After that, six datasets, named S1 to S6, were randomly selected from the training set to train the IPSO-FNN model, and the six training datasets contained 300, 400, 500, 600, 700, and 800 samples, respectively, as shown in Table 2. Among the six datasets, any two training datasets did not intersect. In the same way, six datasets were randomly selected from the testing set to test the IPSO-FNN model, and each testing dataset was composed of 100 samples.

| Dataset Number | Notation | Training Samples | Testing Samples |
|----------------|----------|-------------------------|------------------------|
| 1 | S_1 | 300 | 100 |
| 2 | S_2 | 400 | 100 |
| 3 | S_3 | 500 | 100 |
| 4 | S_4 | 600 | 100 |
| 5 | S_5 | 700 | 100 |
| 6 | S_6 | 800 | 100 |

| Iddle 2. The selected Six datase | Table | 2. | The | selected | six | datasets |
|---|-------|----|-----|----------|-----|----------|
|---|-------|----|-----|----------|-----|----------|

In the experiment, IPSO-FNN was evaluated by comparing it with PSO-FNN (optimizing the parameters of FNN with basic PSO), GA-FNN (optimizing the parameters of FNN with a genetic algorithm), a single FNN, a BPNN (back-propagation neural network), and a SVR (support vector regression) on the evaluation of shearer health condition. The parameters of all optimization algorithms were selected as follow: population size: 50, maximal iteration: 200, the error precision: 0.0001. In IPSO-FNN and PSO-FNN models, $\alpha_{max} = 0.9$, $\alpha_{min} = 0.4$, $c_1 = 1.5$, $c_2 = 2.5$, $[V_{min}, V_{max}] = [-1, 1]$, H = 1. In GA-FNN model, the crossover probability and mutation probability were set to 0.8 and 0.05, respectively. For the single FNN and BPNN models, the number of nodes in the input layer was four, while there was only one output, so k = 4. The number of neurons in the hidden layer n was determined by $\sqrt{k} + a$, where a is a constant between one and 15. Through repeated training tests, n was set to five in this paper. The learning rate was set to 0.05. For the SVR, the LIBSVM package developed by Chang and Lin in Taiwan University was used to construct the SVR model.

In order to compare the advantages and disadvantages of the different methods quantitatively, five indices, including the mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), Theil's inequality coefficient (TIC), and training time (TT), were employed in this paper. The experiment results based on different methods are listed in Table 3. Additionally, the performance comparisons of the six models in MSE, MAE, MAPE, and TIC are illustrated in Figures 4–8.

| Models | Indices | | | Data | asets | | |
|----------|---------|------------|--------|------------|------------|------------|------------|
| widdels | marces | S 1 | S2 | S 3 | S 4 | S 5 | S 6 |
| | MSE | 0.0089 | 0.0085 | 0.0079 | 0.0074 | 0.0084 | 0.0085 |
| | MAE | 0.0653 | 0.0619 | 0.0536 | 0.0516 | 0.0571 | 0.0556 |
| IPSO-FNN | MAPE | 2.41% | 2.23% | 2.09% | 2.05% | 2.14% | 2.11% |
| | TIC | 0.0109 | 0.0095 | 0.0083 | 0.0075 | 0.0086 | 0.0088 |
| | TT (s) | 5.75 | 6.81 | 8.18 | 8.96 | 9.62 | 10.95 |
| | MSE | 0.0098 | 0.0093 | 0.0089 | 0.0081 | 0.0093 | 0.0092 |
| | MAE | 0.0715 | 0.0684 | 0.0617 | 0.0608 | 0.0622 | 0.0624 |
| PSO-FNN | MAPE | 2.86% | 2.74% | 2.55% | 2.51% | 2.57% | 2.54% |
| | TIC | 0.0129 | 0.0112 | 0.0094 | 0.0081 | 0.0090 | 0.0092 |
| | TT (s) | 5.23 | 6.78 | 7.54 | 8.67 | 9.77 | 10.23 |
| | MSE | 0.0097 | 0.0094 | 0.0091 | 0.0079 | 0.0089 | 0.0091 |
| | MAE | 0.0719 | 0.0708 | 0.0671 | 0.0611 | 0.0629 | 0.0622 |
| GA-FNN | MAPE | 2.89% | 2.83% | 2.68% | 2.55% | 2.61% | 2.56% |
| | TIC | 0.0133 | 0.0104 | 0.0091 | 0.0083 | 0.0092 | 0.0094 |
| | TT (s) | 5.86 | 7.01 | 7.97 | 8.84 | 10.12 | 11.08 |
| | MSE | 0.0135 | 0.0115 | 0.0109 | 0.0095 | 0.0102 | 0.0106 |
| | MAE | 0.0912 | 0.0901 | 0.0841 | 0.0810 | 0.0853 | 0.0846 |
| FNN | MAPE | 3.65% | 3.52% | 3.48% | 3.29% | 3.36% | 3.34% |
| | TIC | 0.0157 | 0.0124 | 0.0108 | 0.0101 | 0.0112 | 0.0110 |
| | TT (s) | 12.85 | 14.22 | 15.14 | 16.20 | 17.13 | 18.78 |
| | MSE | 0.0128 | 0.0112 | 0.0106 | 0.0096 | 0.0097 | 0.0098 |
| | MAE | 0.0901 | 0.0867 | 0.0855 | 0.0816 | 0.0844 | 0.0837 |
| BPNN | MAPE | 3.64% | 3.53% | 3.50% | 3.31% | 3.40% | 3.39% |
| | TIC | 0.0148 | 0.0121 | 0.0106 | 0.0098 | 0.0106 | 0.0104 |
| | TT (s) | 11.55 | 13.95 | 15.66 | 16.53 | 17.64 | 18.94 |
| | MSE | 0.0125 | 0.0119 | 0.0102 | 0.0097 | 0.0096 | 0.0098 |
| | MAE | 0.0894 | 0.0867 | 0.0806 | 0.0768 | 0.0759 | 0.0761 |
| SVR | MAPE | 3.56% | 3.52% | 3.49% | 3.26% | 3.22% | 3.31% |
| | TIC | 0.0134 | 0.0125 | 0.0101 | 0.0098 | 0.0101 | 0.0099 |
| | TT (s) | 12.02 | 13.85 | 14.64 | 15.95 | 17.01 | 17.58 |



Figure 4. Comparison of mean square error.



Figure 5. Comparison of mean absolute error.



Figure 6. Comparison of mean absolute percentage error.



Figure 7. Comparison of Theil's inequality coefficient.



Figure 8. Comparison of training time.

As shown in Table 3 and Figures 4–7 we can see that the performance of IPSO-FNN, PSO-FNN, and GA-FNN is better than that of single FNN, BPNN, and SVR. The reason lies in the fact that the parameters of FNN, BPNN, and SVR are not suitable for the models to estimate the shearer health conditions, while the parameters of other FNNs are obtained by the corresponding optimization algorithms. With the improved strategy for PSO, IPSO can obtain better parameters for the FNN and the overall performance of the IPSO-FNN model is better than the other models for health condition estimation. However, the curves in Figure 8 present different performance. The six algorithms will consume more and more training time with the increase of the FNN, the training times of the IPSO-FNN, PSO-FNN, and GA-FNN are obviously shorter than other methods.

In addition, it can be observed from Table 3 and Figures 4–7 that the proposed method provides the best evaluation performance than other methods when the number of the training samples changes from 300 to 800. Four indices of the IPSO-FNN-based, PSO-FNN-based, GA-FNN-based, FNN-based, BPNN-based, and SVR-based evaluation methods decreases at first and then increases or have faint fluctuations with the increase of training samples size. The reason for this phenomenon is that too many training samples may over-train the network and the generalization performance of the network will weaken. Furthermore, the evaluation results of the shearer health condition are not always ideal. Therefore, on the premise of ensuring evaluation performance and running time for the shearer health condition, the number of training samples should be determined according to the actual experiment.

In order to further prove the optimization performance of the proposed IPSO in training the FNN model, the basic PSO [26], quantum-behaved PSO (QPSO) [27], opinion leader-based QPSO (OLB-QPSO) [28], and Laplace PSO (LPSO) [29] were employed to optimize the parameters in the FNN model. The parameters were set according to the relevant literatures. Based on the previous analysis, the dataset of S4 was selected for training and testing the FNN model. Three indices of MSE, MAPE, and TT were used to measure the optimization capacity in the FNN model and the comparison results are listed in Table 4.

| Algorithms | | Training Phase | 2 | Testing Phase | | |
|---------------|--------|----------------|--------|---------------|----------|--|
| 8 | MSE | MAPE (%) | TT (s) | MSE | MAPE (%) | |
| PSO | 0.0056 | 2.24 | 8.67 | 0.0081 | 2.51 | |
| QPSO | 0.0051 | 1.91 | 9.11 | 0.0076 | 2.09 | |
| OLB-QPSO | 0.0039 | 1.81 | 10.24 | 0.0069 | 1.98 | |
| LPSO | 0.0042 | 1.83 | 10.67 | 0.0071 | 2.01 | |
| Proposed IPSO | 0.0047 | 1.86 | 8.96 | 0.0074 | 2.05 | |

Table 4. Performance indices of five algorithms for optimizing the FNN model.

As seen from Table 4, the PSO with some improvements performs better training and testing properties than the basic PSO in optimizing the FNN model. In comparison of the four improved PSO algorithms, the OLB-QPSO can obtain the best MSE and MAPE values, both in the training phase and testing phase, while the training time (10.24 s) is not ideal. Although the MSE and MAPE values of the proposed IPSO are a little larger than those of OLB-QPSO and LPSO, the training time (8.96 s) is obviously better than other three improved PSO algorithms. Offering comprehensive consideration of the prediction error and running time, the proposed FNN-IPSO predictor can perform better in evaluating the shearer health condition.

5. Field Application

In order to illustrate the application effect of the IPSO-FNN model, we and developed built an online system based on the proposed approach and applied it in the field of actual, fully-mechanized coal face, as shown in Figure 9.



Figure 9. Field application example based on the proposed method.

In this field application, the four variables of the shearer were collected and transmitted into the explosion-proof computers via wireless Ethernet in the coal mining face. The procedure of the proposed algorithm was loaded in the explosion-proof computers to process the collected signals and estimate the health condition of the shearer. Synchronously, the results were displayed on the ground monitoring center through the communication station. When the shearer was cutting the coal seam from 50 m to 65 m, the corresponding estimation results were plotted, as shown in Figure 10.



Figure 10. The evaluation results of shearer health condition based on proposed system: (**a**) the coal seam condition; and (**b**) the evaluation results.

As Figure 10 shown, the coal seam from 55 to 65 m could be divided into three categories, among which the coal seam of "Coal 1" was harder than "Coal 2", and "Coal 3" contained some gangues. When the shearer was working in the first coal seam, the evaluation results of the shearer health condition were mostly between health grades 2 and 3. For coal seam "Coal 2", the evaluation results of the shearer health condition could decrease between health grade 1 and 2. For the coal seam with some gangues, the shearer health condition became more undesirable and the evaluation results were around health grade 4.

Based on above analysis, the evaluation results of shearer health condition were consistent with actual coal seam conditions and the proposed system was proved feasible in the evaluation of shearer health condition.

6. Conclusions

Aimed at the existing problems of shearer health condition, this paper comprehensively considers four parameters that affect the health condition of a shearer and proposes an evaluation method

based on the integration of a fuzzy neural network (FNN) and improved particle swarm optimization algorithm (IPSO). To enhance the prediction performance of the FNN, the premature judgment and mutation mechanism were coupled with the PSO algorithm to realize the optimization of FNN parameters. Then, an experimental example is provided and some comparisons with other methods are carried out. The experiment and comparison results show that the proposed approach is feasible and outperforms others. Finally, a field application example is presented to indicate that the shearer health condition can be accurately and expediently evaluated in the actual condition.

In future studies, the authors will consider other potential parameters that affect the shearer health condition to further improve the prediction results. In addition, other predictors with improved intelligence algorithms will be developed to obtain better performance.

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