

Quantitative identification of wire rope core conveyor belt damage based on GWO-BP

Guoxin Sun^{1,2}, Xinpeng Du¹,
Jianlong Zhang³, Runze Zhang¹ and
Qihui Yu^{1,*}

¹School of Mechanical Engineering,
Inner Mongolia University of
Science and Technology, Baotou
014010, China

²Key Laboratory of Intelligent
Diagnosis and Control of
Electromechanical Systems, Inner
Mongolia Autonomous Region,
Baotou 014010, China

³North Intelligent Energy Research
Institute, Mingyang, Inner Mongolia

*E-mail: yuqihui@imust.edu.cn

Received for publication
September 11, 2024.

Abstract

To address the challenges of detecting internal damage in steel wire rope core conveyors and the difficulties in quantitative identification, this study proposes an improved backpropagation (BP) neural network damage identification algorithm based on the Grey Wolf Optimization (GWO-BP). The Grey Wolf algorithm is employed to optimize the initial weights and thresholds of the BP neural network, thereby enhancing its performance and stability. A testing apparatus for detecting damage in steel wire rope core conveyors is designed and constructed to evaluate the algorithm's effectiveness and feasibility. First, damage signal data from the steel wire rope are extracted and normalized to facilitate the convergence of the predictive model. Next, the BP neural network algorithm is optimized to address issues such as parameter selection randomness, improving model training speed and identification accuracy. Experimental results indicate that the optimized BP algorithm achieves an average identification accuracy of 96.0%, representing a 5.5% improvement over the unoptimized BP algorithm and significantly enhancing the precision of damage quantitative identification.

Keywords

Steel wire rope core conveyor, BP neural network, Grey Wolf algorithm, quantitative identification

1. Introduction

Steel wire rope core conveyors, as crucial load-bearing components, exhibit characteristics such as high strength, abrasion resistance, and corrosion resistance. They are commonly utilized in industries, including mining, ports, metallurgy, and construction for material transport [1–3]. Over prolonged use, factors such as tensile bending, alternating loads, and harsh environments inevitably lead to various forms of damage, such as fatigue cracks, wear, and fractures, which significantly impact the lifespan and safety of the conveyors. Therefore, accurately and effectively detecting internal damage in steel wire rope core conveyors is essential for ensuring their safety and operational longevity [4–6].

The most common damage occurs within the steel wire rope itself. Thus, the focus is on the quantitative identification of wire rope damage. Numerous scholars have actively explored this field, proposing various non-destructive testing methods. Ping et al. [7] introduced an enhanced visual sensor-based intelligent detection method for surface damage in steel wire ropes using advanced machine vision sensors. Shiwei et al. [8] combined Hall sensors with magnetic flux leakage detection to assess surface damage, thereby mitigating external interference. Zhen et al. [9] proposed an adaptive moving average filtering method to allocate optimal parameters for detecting surface damage signals. Wei et al. [10] employed longitudinal wave sensors to detect tension changes in steel wire ropes, selecting excitation frequencies

based on inherent frequency detection results for surface damage identification. Zeng Guang et al. [11] developed a magnetic memory detection platform under weak magnetic fields, utilizing infrared image defect extraction methods for quantitative identification of steel wire rope damage. Liu et al. [12] proposed a novel magnetic flux leakage imaging method to effectively reduce interference under complex conditions for quantitative damage detection. However, these damage identification methods primarily rely on manual feature extraction from signals, necessitating substantial experiential knowledge for processing and analyzing raw data, and feature extraction is often limited by external interference.

In recent years, deep learning neural network theories have found widespread application across various fields. Mohamed et al. [13] presented a supervised regression deep learning model for predicting real estate prices, effectively reducing model prediction errors through parameter adjustment and optimization. Setiawan et al. [14] developed a sequence-to-sequence prediction model based on deep learning, implementing the Luong attention mechanism, commonly used in NLP research, for time series forecasting. Many scholars have conducted extensive research on the quantitative identification of steel wire rope damage using deep learning theories. Deep learning leverages its supervised backpropagation (BP) algorithm for optimization and adjustment, enabling automatic extraction of fault feature information from raw signals without human interference, converting them into abstract features conducive to classification. BP neural networks possess non-linear mapping and adaptability, resulting in high classification accuracy; they establish relationships between the characteristics of broken wire signals and steel wire rope damage signals, facilitating quantitative identification of wire rope damage [15–17]. Zhou et al. [18] introduced a single-channel signal processing method in the time-frequency domain, constructing a BP neural network to extract multiple sets of time-domain features as input for damage identification. Qiang et al. [19] employed the HOG algorithm to extract damage features and combined BP neural networks with support vector machines for quantitative identification. Liancheng et al. [20] proposed a method for recognizing internal and external broken wire damage in steel wire ropes by collecting magnetic flux leakage signals generated by damage and inputting them into a BP neural network for classification. Yiqing et al. [21] enhanced damage identification accuracy by combining continuous wavelet transform (CWT) with

BP neural networks, converting one-dimensional signals into two-dimensional signals. Dong et al. [22] introduced a steel wire rope damage recognition method that combines adaptive moving average noise reduction with BP neural networks, employing particle swarm optimization (APSO) to determine optimal window widths and normalize output feature samples before inputting them into the BP neural network for damage identification. Shiwei and Muchao [23] proposed a steel wire rope damage identification method based on magnetic flux leakage and BP neural networks, utilizing Haar wavelet transform and differential operations for noise reduction, thus enhancing recognition accuracy. Yang et al. [24] introduced a damage identification method that combines model-driven and data-driven algorithms, integrating boundary element methods with BP neural networks for high-precision detection. Most of these methods are based on feature vectors extracted from signal characteristics, which are subsequently input into BP neural networks for training, ultimately achieving quantitative identification of steel wire rope damage. However, the output layer of BP neural networks often reduces high-dimensional feature spaces to lower dimensions, inevitably leading to information loss.

Additionally, BP neural networks face issues such as slow convergence, susceptibility to local extrema, and randomness in initial weight and hyperparameter selection, hindering accurate quantitative identification of steel wire rope damage. To address this pressing issue, intelligent algorithms can optimize the initial weights and hyperparameters of BP neural networks, overcoming drawbacks like vulnerability to local extrema, slow convergence, and sample dependence [25,26]. Jinyu et al. [27] proposed a damage identification method based on particle swarm-backpropagation (PSO-BP) neural networks, enhancing detection accuracy compared to traditional BP neural networks; however, the PSO algorithm is sensitive to parameter selection and may converge to local optima, making its convergence and stability analysis relatively challenging [28,29]. The Grey Wolf Optimizer (GWO) mimics the cooperative behavior of wolf packs to achieve optimization, featuring adaptive convergence factors and an information feedback mechanism that balances global search and local optimization, with a straightforward structure and minimal parameters, excelling in both solution accuracy and convergence speed [30–32].

In summary, this paper proposes a quantitative identification method for damage in steel wire rope core conveyors based on a GWO-BP neural network.

By extracting broken wire signals from the damage signals, the GWO algorithm improves the BP neural network, reducing training parameters and time while accurately predicting the number of broken wires, thereby significantly enhancing identification precision and achieving quantitative damage identification. Experimental results demonstrate that the proposed research strategy offers high accuracy and rapid identification speed for steel wire rope core conveyor damage, validating the effectiveness of this algorithm and providing a novel solution for the quantitative identification of such damage.

II. Theoretical Background

a. BP neural network algorithm

The BP neural network comprises two subprocesses: the forward propagation of working signals and the backward propagation of error signals. It consists of an input layer, an output layer, and several hidden layers. Each sample in the BP neural network has a certain number of inputs and outputs, allowing for a theoretical mapping from one-dimensional space to another using a three-layer neural network [33–35]. The number of nodes in the hidden layer is the only variable in the BP neural network, and its selection significantly impacts the network's performance. Initially, the number of hidden layer nodes can be estimated using an empirical formula, expressed as follows:

$$h = \sqrt{m + n} + a \quad (1)$$

where h represents the number of hidden layer nodes, m represents the number of input layer nodes, n represents the number of output layer nodes, and a represents the adjustment constant, with a range of 0–10. In this study, it is chosen between 2 and 12.

Let i represent the weight between node j and node w_{ij} , and j denote the threshold of node b_j . Each node's output value is denoted as x_j . The output value of each node is determined by the weights from the current node to all nodes in the previous layer, the threshold of the current node, and the output values of all nodes in the activation function. The computation process is as follows:

$$S_j = \sum_{i=0}^{m-1} w_{ij} x_i + b_j \quad (2)$$

$$x_j = f(S_j) \quad (3)$$

where f represents the activation function, typically selected as either a linear function or a sigmoid function.

b. GWO algorithm

The GWO algorithm has been successfully applied in various domains, including shop scheduling, parameter optimization, and image classification. When enhancing BP neural networks, the GWO algorithm effectively identifies optimal solutions by simulating the social hierarchy, tracking, surrounding, and attacking behaviors of wolf packs. While the particle swarm optimization (PSO) algorithm is also suitable for parameter optimization, it does not perform as well as GWO in terms of parameter sensitivity and convergence speed. As illustrated in Figure 1, the convergence speed and mean squared error of the GWO algorithm are superior to those of the PSO across different iterations, highlighting the distinct advantages of the GWO in optimizing BP neural network performance [36,37].

The GWO algorithm emulates the hunting behavior of wolf packs, which operate under a strict hierarchical structure divided into four ranks: α , β , δ , and ω [38], as illustrated in Figure 2.

First Layer: α -level Wolf pack. This layer comprises the leaders within the wolf population, tasked with guiding the entire pack in hunting prey and seeking the optimal solution in the optimization algorithm.

Second Layer: β -level Wolf pack. These wolves support the α -level wolf pack and represent suboptimal solutions within the optimization algorithm.

Third Layer: δ -level Wolf pack. This layer follows the instructions and choices of the α and β levels,

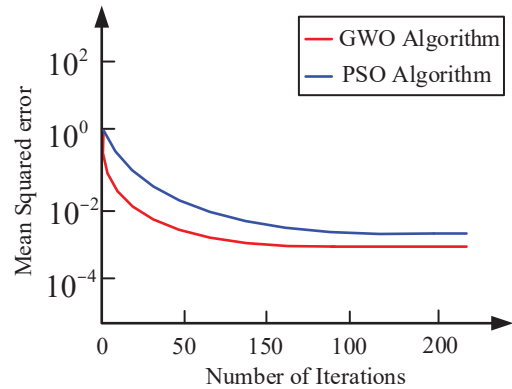


Figure 1: Performance difference between GWO and PSO. GWO, grey wolf optimizer; PSO, particle swarm optimization.

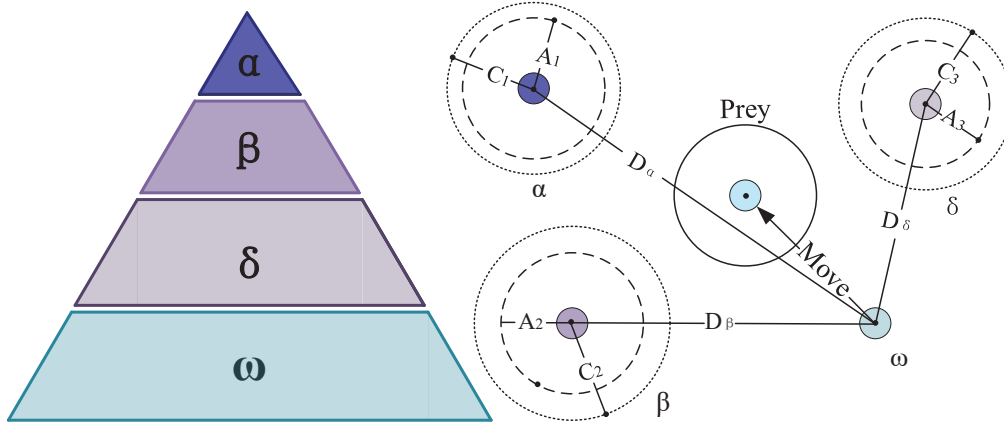


Figure 2: Hierarchy of grey wolves.

tasked with reconnaissance and surveillance duties. α and β wolves with lower fitness levels are demoted to the δ level.

Fourth Layer: ω -level Wolf pack. These wolves orbit around the α , β , or δ levels for positional updates.

When mathematically modeling the social hierarchy of wolves in GWO, the three best wolves (optimal solutions) are defined as α , β , and δ , leading the other wolves in search of the target. The remaining wolves (candidate solutions) are designated as ω , which update their positions around α , β , and δ [39]. In nature, the hunting process of wolf packs is typically led by the alpha wolf, while other ranks coordinate to protect, pursue, and attack the prey (the optimal solution), whose location remains unknown during the actual evolutionary process. Thus, in the GWO algorithm, the optimal wolf is assigned as α , the second-best as β , the third as δ , and the rest as ω .

A model is established based on the characteristic that α , β , and δ possess more knowledge about the prey's location. During iterations, α , β , and δ guide the movements of ω to achieve global optimization. The equations for updating the positions of all grey wolves are as follows:

$$\begin{cases} \overline{D}_\alpha = |\overline{C}_1 * \overline{X}_\alpha - \overline{X}| \\ \overline{D}_\beta = |\overline{C}_2 * \overline{X}_\beta - \overline{X}| \\ \overline{D}_\delta = |\overline{C}_3 * \overline{X}_\delta - \overline{X}| \end{cases} \quad (4)$$

Where $\overline{X}_\alpha$ is the position of α , $\overline{X}_\beta$ is the position of β , $\overline{X}_\delta$ represents the position of δ , $\overline{D}_\alpha$ represents the distance of the ω wolf individual to the α -level wolf pack, $\overline{D}_\beta$ represents the distance of the ω wolf

individual to the β -level wolf pack, and $\overline{D}_\delta$ represents the distance of the ω wolf individual to the δ -level wolf pack.

The adjustments of the ω wolves' positions under the influence of α , β , and δ are calculated as follows:

$$\begin{cases} \overline{X}_1 = |\overline{X}_\alpha - A_1 * \overline{D}_\alpha| \\ \overline{X}_2 = |\overline{X}_\beta - A_2 * \overline{D}_\beta| \\ \overline{X}_3 = |\overline{X}_\delta - A_3 * \overline{D}_\delta| \end{cases} \quad (5)$$

Where $\overline{X}_1$ represents the position adjusted by the influence of the α -level wolf pack on the ω -level wolf, $\overline{X}_2$ represents the position adjusted by the influence of the β -level wolf pack on the ω -level wolf, and $\overline{X}_3$ represents the position adjusted by the influence of the δ -level wolf pack on the ω -level wolf.

The average is taken as follows:

$$\overline{X}(t+1) = \frac{\overline{X}_1 + \overline{X}_2 + \overline{X}_3}{3} \quad (6)$$

When the value of α decreases from 2 to 0, the corresponding value of A will change within the range of $[-\alpha, \alpha]$. If α is set too high, it may cause the wolves to stray from the prey, necessitating a global search of the wolf pack ($|A| > 1$). If set too low, it may lead the wolves too close to the prey, necessitating a local search of the wolf pack ($|A| < 1$).

$$a = 2 - \frac{2 \cdot t}{T} \quad (7)$$

Where t is the current iteration count and T is the predefined maximum iteration count.

c. GWO-BP-based damage identification algorithm

The flowchart for the GWO-BP algorithm used for the quantitative identification of damage in wire rope core conveyor belts is illustrated in Figure 3. Initially, damage signals related to broken wires are collected using a constructed detection platform. The signals are then subjected to filtering and noise reduction, followed by feature extraction to establish a training dataset for the neural network. Finally, the GWO algorithm is employed to optimize the initial weights and thresholds of the BP neural network, resulting in the GWO-BP damage identification model.

The optimization process based on GWO-BP is depicted in Figure 4. In optimizing the BP neural network using the GWO algorithm, the positions of the grey wolves are set as the initial weights and

thresholds of the BP neural network. During each iteration, the three wolves with the best fitness values are designated as the leading wolves, whose positions are used to update the positions of the remaining individuals in the pack. This continual assessment of the prey's location allows for the iterative updating of weights and thresholds in the BP neural network, ultimately converging on optimal results.

The specific optimization steps are as follows:

1. Determine the initial structure of the BP neural network, including the number of nodes in the input layer (4), hidden layer (4), and output layer (1).
2. Initialize parameters: Set the population size of grey wolves (SN) to 20, with upper (ub) and lower (lb) bounds of 2 and -2, respectively, and a maximum iteration count (max Iter) of 100. Calculate the dimensionality of the Grey Wolf positions based on the network structure and randomly initialize their locations.
3. Map the Grey Wolf positions to the BP neural network and compute fitness values according to the specified formulas.
4. Fitness value computation: Classify the wolf pack into four groups— α , β , δ , and ω —based on rank and update the grey wolves' position information and the values of parameters a , A , and C using formulas (4)–(6).
5. Assess the boundary conditions of each Grey Wolf's dimensions; if any dimensions exceed their bounds, adjust the respective upper or lower bounds accordingly.
6. Check the iteration count: If it is less than the maximum iterations, repeat steps (2) through (5) until the conditions are met; otherwise, terminate the algorithm.
7. Construct the GWO-BP neural network: Assign the optimized weights and thresholds as the initial parameters of the BP neural network, completing the network's construction.
8. Output the prediction of broken wire counts: Input the existing feature dataset into the GWO-BP network model, with the output representing the predicted number of broken wires.

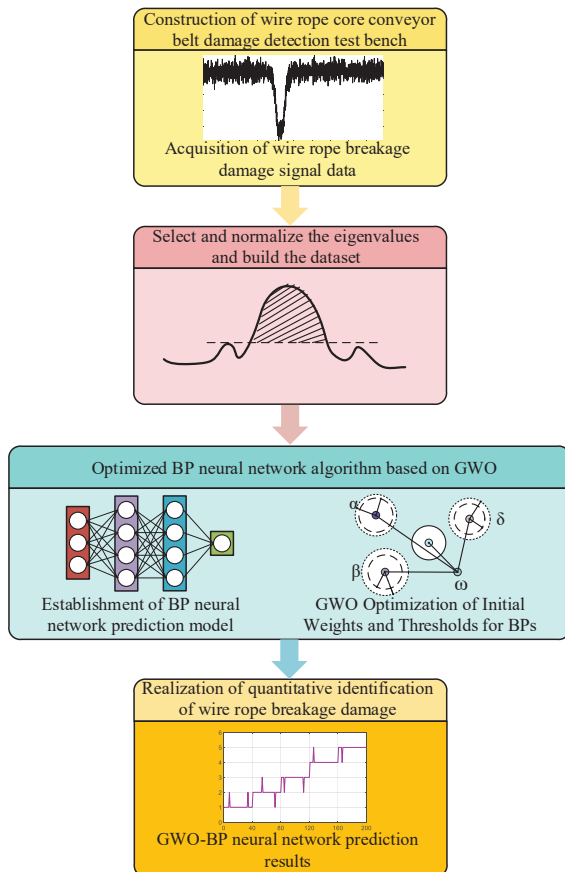


Figure 3: Quantitative damage identification method for wire rope core conveyor belts based on GWO-BP. BPs, backpropagations; GWO, grey wolf optimizer.

III. Experimental Data Collection

a. Detection platform for wire rope core conveyor belts

The system composition of the experimental platform is shown in Figure 5. The mainframe consists

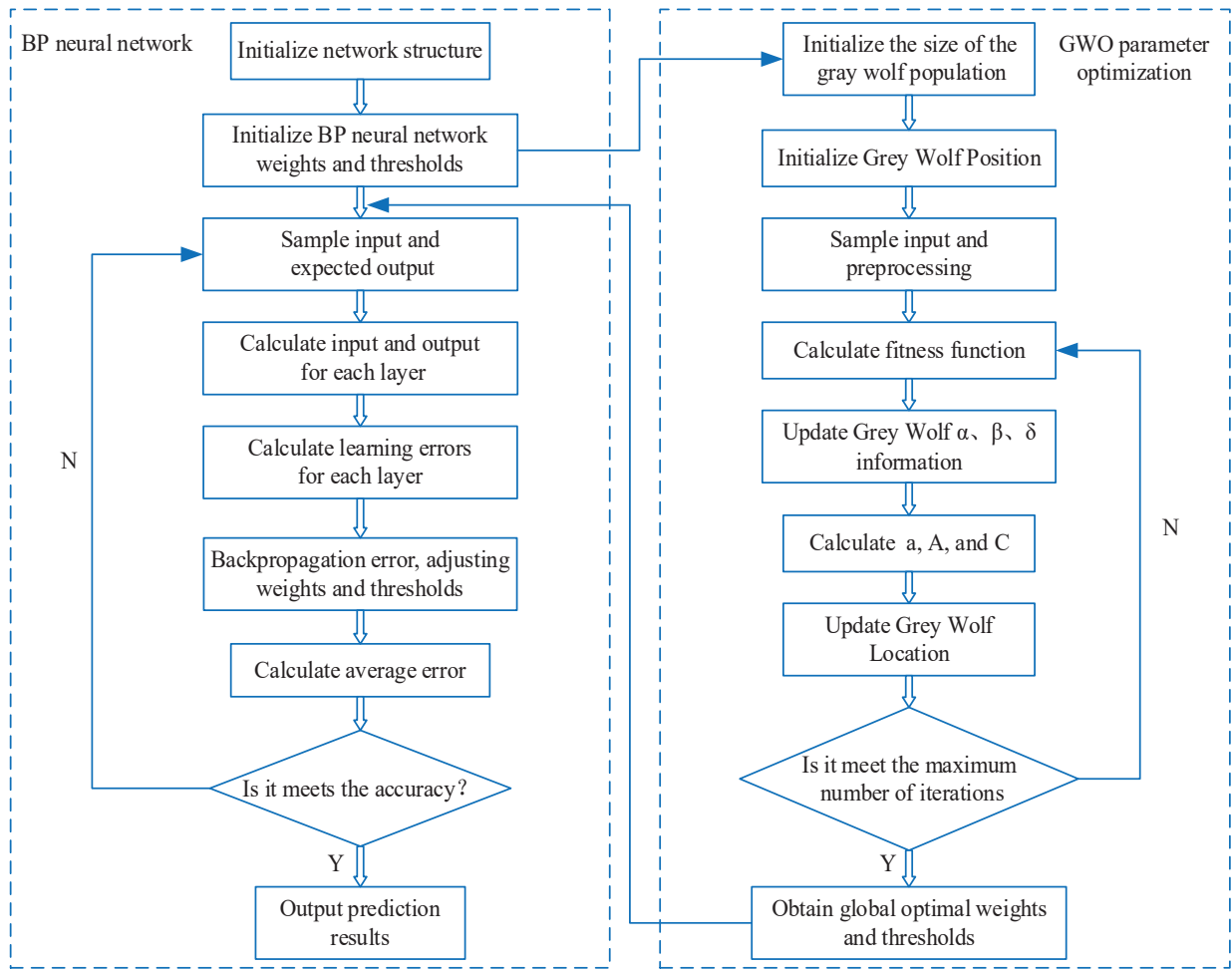


Figure 4: Optimization flowchart based on GWO-BP. BP, backpropagation; GWO, grey wolf optimizer.

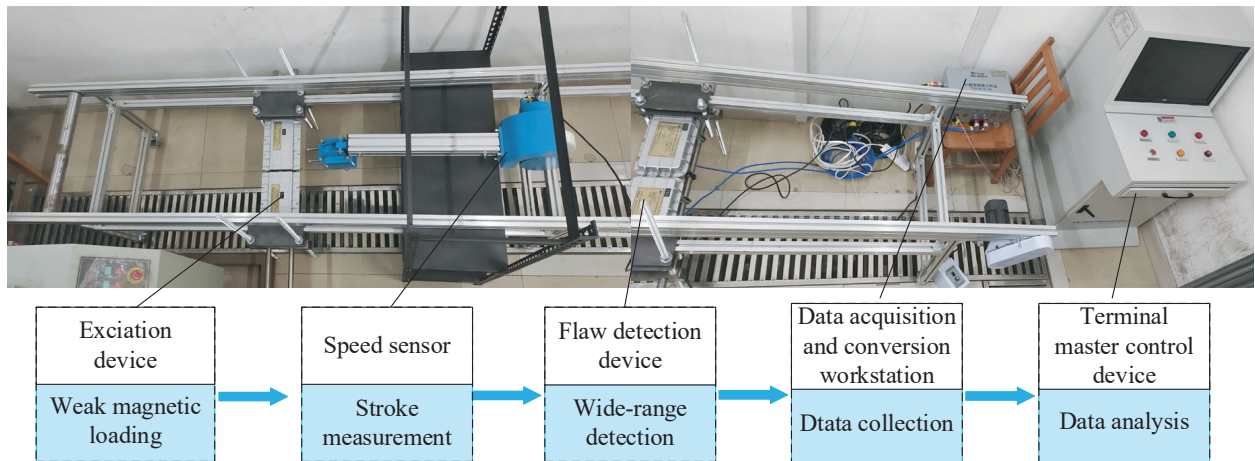


Figure 5: Detection platform for internal damage in wire rope core conveyor belts.

Table 1: Experimental instruments and main parameters

Serial number	Experiment instrument	Quantity	Model	Rated voltage
1	Excitation device	2	RC300	/
2	Speed sensor	1	GS10 (A)	DC12V
3	Injury detection sensors	2	GTSC300	DC5V
4	Digital mining conversion workstation	1	TCK.W-AI-E9	AC220V
5	Terminal master control unit	1	TCK.W-ZK1200-D	AC127V

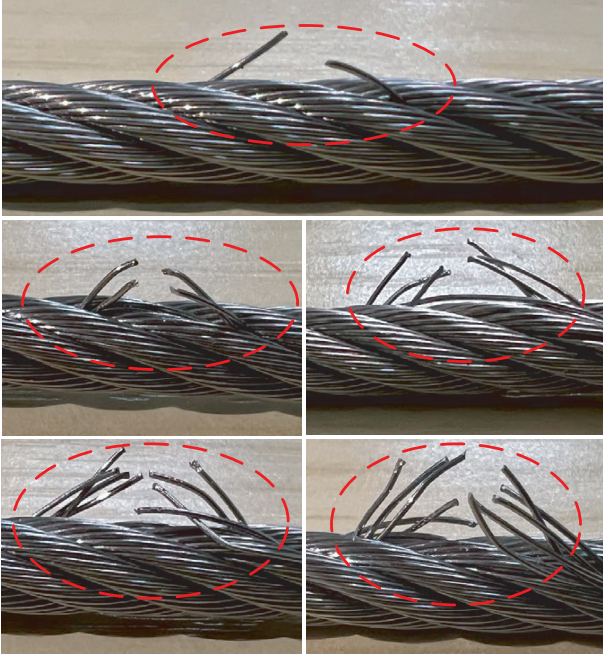


Figure 6: Samples of wire breakage damage.

of two layers, with the lower layer designated for the installation of magnetic planning devices and flaw detection sensors, ensuring a separation of over 2 m. Additionally, the height between the detection sensors and the upper layer belt must range from 3 cm to 15 cm. The upper layer houses a motor that drives the movement of the conveyor model, capable of providing multiple speed settings. The conveyor model can be cut to any desired length and is securely fastened at both ends. The entire sample moves in a translational manner, with a roller-type speed sensor installed above. The instruments and parameters used in the experiment are detailed in Table 1.

b. Extraction of damage features from wire rope core conveyor belts

To achieve quantitative damage identification, it is essential to create artificially damaged samples of the wire rope core. The specifications chosen for the wire rope core are a diameter of 6 mm and material made from high-carbon steel. Five different types of wire breakage damage models were produced, as illustrated in Figure 6.

After denoising the collected raw signals, clear damage signals can be observed at the damaged locations. To enhance the accuracy of damage prediction while reducing the complexity of data processing, it is necessary to extract easily manageable feature parameters that require minimal data and computational time. Through feature analysis of the leakage magnetic signals at the breakage points, the signal peak value, signal width, area under the waveform, and wavelet energy were selected as features for quantitative damage identification, as shown in Figure 7.

c. Normalization of damage signals

Before training the neural network with the broken wire signal data, normalization of the feature values is required. This entails determining the maximum and minimum values for a given feature and subsequently rescaling its values to a range within [0,1]. The normalization transformation formula is used as follows:

$$x'_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (8)$$

Where x_i represents a specific data point of a feature value and x'_i is the normalized data.

The experimental platform is utilized to collect broken wire signal data, which undergoes denoising

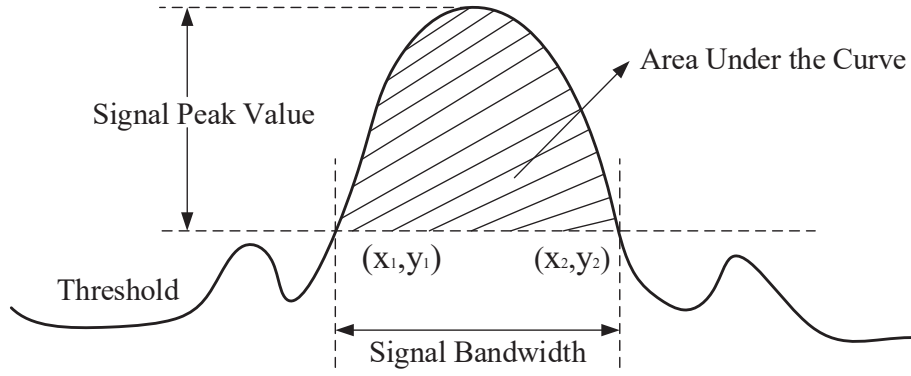


Figure 7: Schematic diagram of feature values for steel cord damage signals.

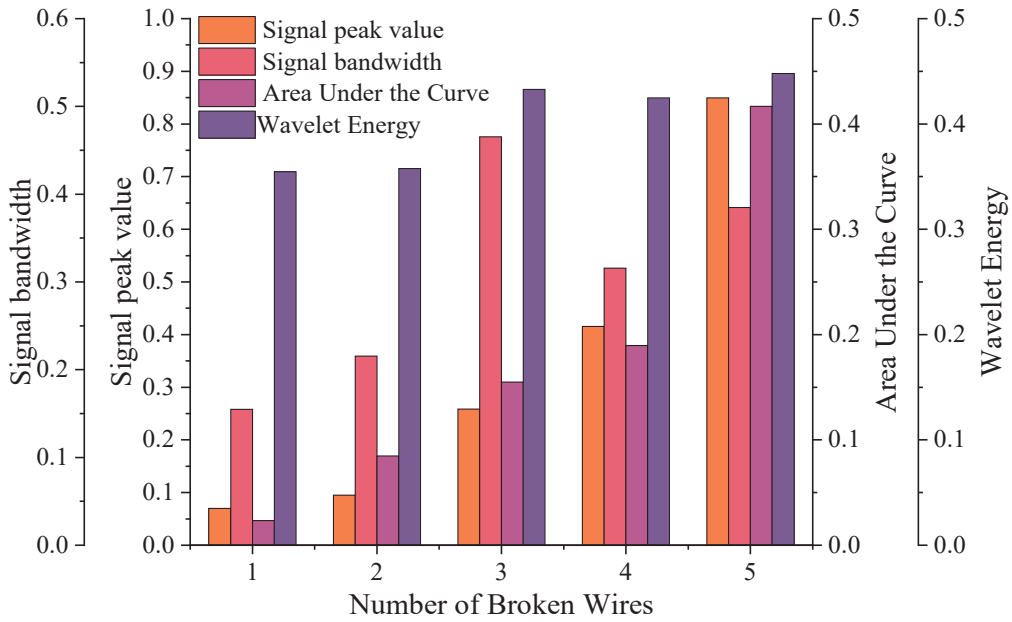


Figure 8: Local feature values of broken wires in the wire rope.

and normalization, resulting in 700 sets of feature values. Among these, 140 sets correspond to broken wire counts of 1, 2, 3, 4, and 5, with 100 sets from each feature used for neural network training, while the remaining 200 sets are reserved for subsequent model identification and classification predictions, as illustrated in Figure 8.

IV. Analysis of Experimental Results

Based on the number of feature values and network requirements, the input layer, hidden layer, and output layer of the BP neural network were set to 4, 4, and 1 nodes, respectively, with the S-shaped

activation function ($\tanh$) selected. The training function employed was the Levenberg–Marquardt algorithm, known for its low complexity and rapid convergence. After 200 iterations, 100 normalized feature value sets for each of the 1–5 broken wire scenarios, totaling 500 sets, were prepared, with 70% allocated to the training set and 30% to the testing set. Figure 9 displays the regression results of the BP neural network, with all regression outcomes exceeding 0.99.

To compare the classification effectiveness between the BP and GWO-BP neural networks, 40 feature value sets for each broken wire count (1–5) were input into both predictive models, resulting in the classification error illustrated in Figure 10. The vertical

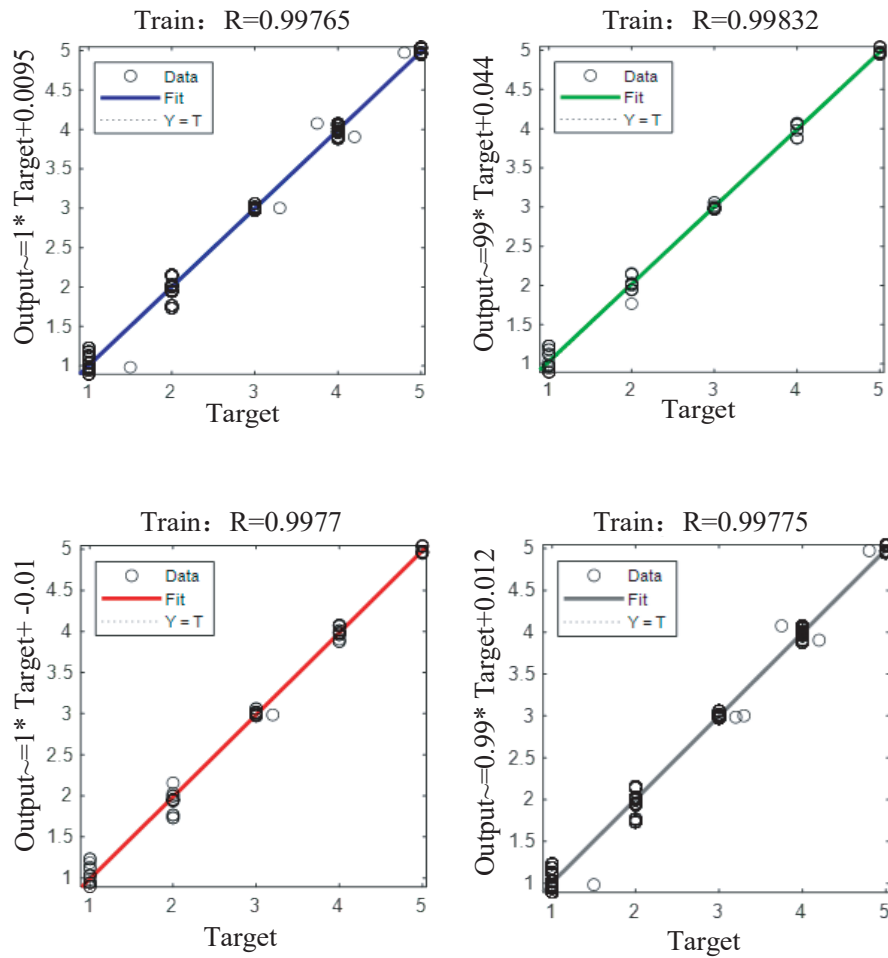


Figure 9: Regression results of the dataset.

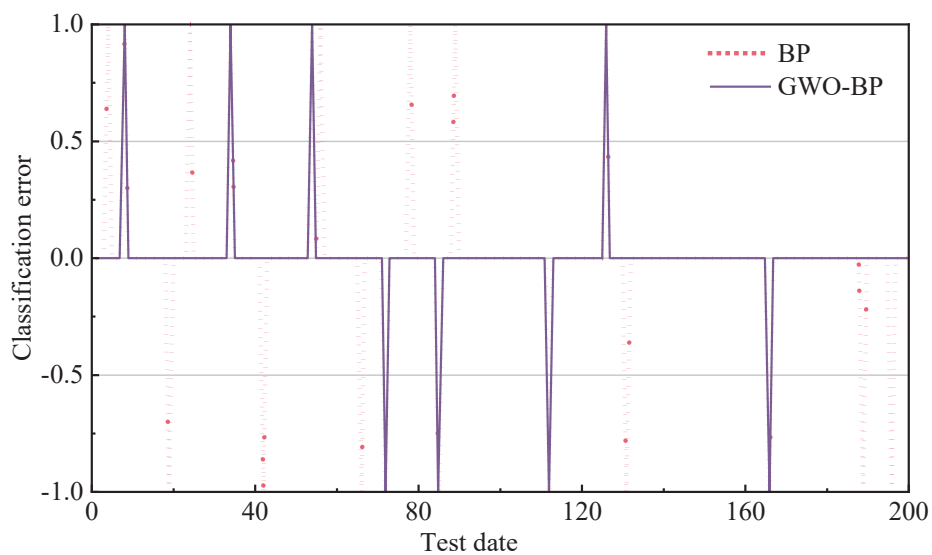


Figure 10: Classification errors of two prediction models. BP, backpropagation; GWO, grey wolf optimizer.

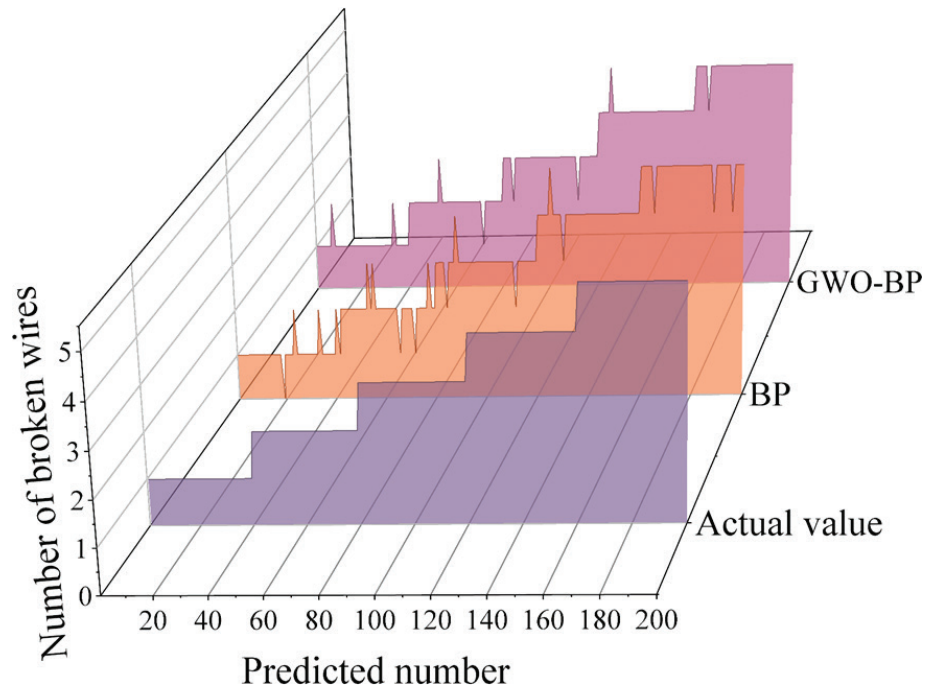


Figure 11: Classification and recognition performance of two neural network prediction models.

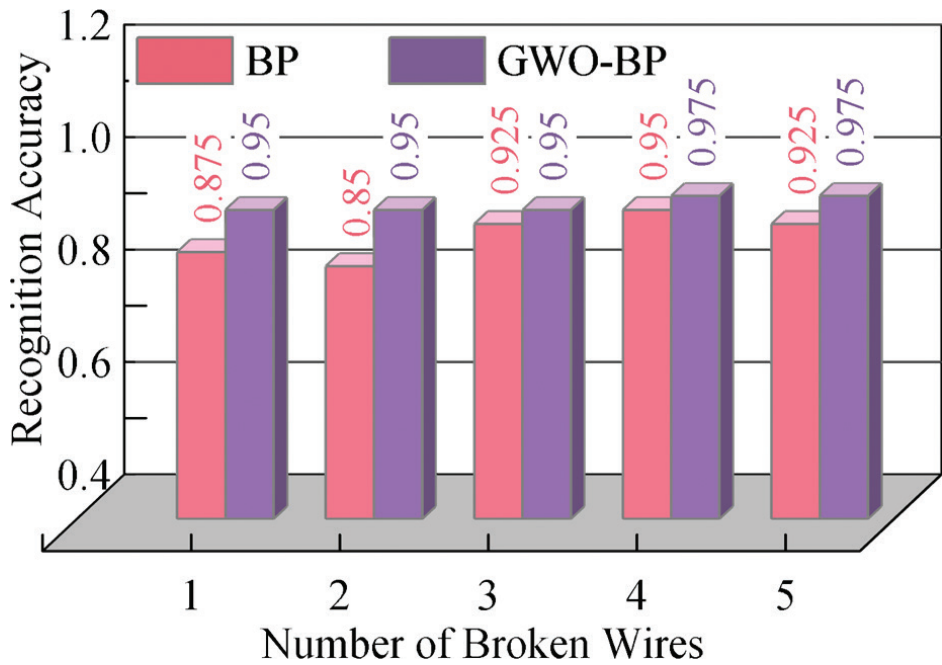


Figure 12: Recognition accuracy of two prediction models under different numbers of broken threads. BP, backpropagation; GWO, grey wolf optimizer.

axis represents the difference between predicted and actual values—0 indicates equality, 1 signifies that the predicted value exceeds the actual, and -1 indicates the opposite. The horizontal axis delineates the actual

broken wire counts (1–5) with their corresponding 40 sets of predicted data.

Observing the classification results reveals that both predictive models perform admirably;

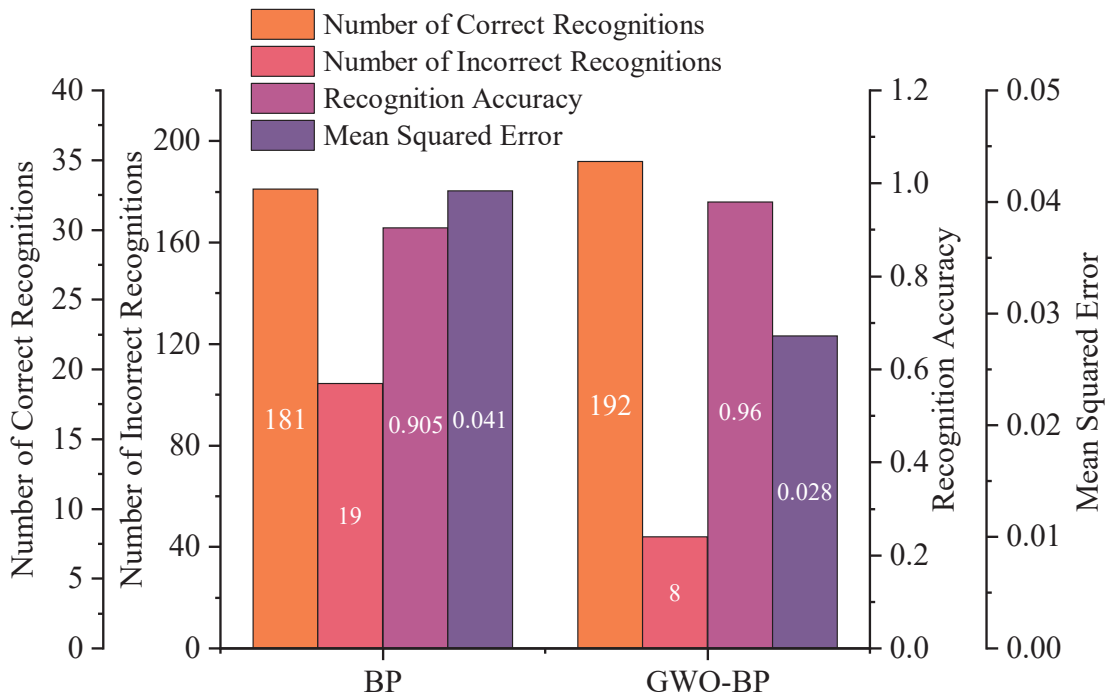


Figure 13: Comparison of damage quantification identification between two prediction models. BP, backpropagation; GWO, grey wolf optimizer.

however, the BP neural network model experienced 6 prediction errors when the actual broken wire count was 2, with the fewest errors occurring when the count was 4. The optimization of the BP neural network using the GWO algorithm led to significant improvements in classification accuracy, although there were still 2 errors for actual counts of 1, 2, and 3. Overall, the GWO-BP neural network exhibited smaller prediction errors and greater accuracy. The performance of both neural network models is depicted in Figure 11.

In Figure 11, the horizontal axes 0–40, 41–80, 81–120, 121–160, and 161–200 are the 40 sets of prediction data corresponding to the actual number of broken wires of 1, 2, 3, 4, and 5, and it can be seen that the prediction effect of the GWO-BP neural network is significantly better than that of the BP neural network, and the prediction accuracy is significantly improved through Figures 11 and 12. When the actual number of broken wires is 1 and 2, the correct rate of BP neural network prediction and identification is low, not reaching 90%; when the actual number of broken wires is 3, 4, and 5, the correct rate of prediction and identification is relatively high. The prediction and identification effect based on the GWO-BP neural network is better than that of the BP neural network

under the conditions of the number of broken wires, and the prediction rate of the quantitative damage identification model is 95.0% and above, with high prediction accuracy.

As illustrated in Figure 13, both the BP and GWO-BP neural network models attained recognition accuracy exceeding 90% when trained on 500 sets and predicting 200 sets of data. The GWO-optimized BP neural network achieved optimal initial weight and threshold vectors, resulting in a prediction accuracy of 96.0%, which represents a 5.5% improvement over the pre-optimization BP model, thereby validating the effectiveness of the GWO optimization algorithm.

V. Discussion

This study investigates the widespread application and limitations of the BP neural network algorithm in detecting wire rope damage, proposing a novel quantitative identification method for internal damage in wire rope core conveyor belts based on the GWO-BP neural network. This approach optimizes the conventional BP neural network algorithm, enhancing its detection performance. Experimental results demonstrate a significant improvement in damage

recognition accuracy compared to the standard BP neural network. While existing PSO-enhanced BP neural networks have improved accuracy, the PSO algorithm's complexity and sensitivity to parameter selection often lead to local optima, making convergence and stability analysis challenging. In contrast, the GWO algorithm exhibits robust global search capabilities, rapid convergence, and superior optimization precision, thereby offering a distinct advantage in optimizing BP neural networks.

The proposed GWO-BP neural network method shows excellent performance in quantitatively identifying wire rope damage, but testing has only been conducted under laboratory conditions. In real-world scenarios, the spatial positioning, quantity, size, and shape of slag on conveyor belts remain uncertain and random. Current efforts are underway to simulate actual working conditions and conduct extensive testing, ensuring that data collection and damage recognition accuracy more closely reflect real situations. Future research could explore the simulation and experimental validation of conveyor belt models under various slag conditions. Additionally, further investigations may examine the effects of slag quantity and iron content, wire rope iron content, and conveyor belt specifications on the proposed damage detection method. This study could also explore the influence of external magnetic fields on magnetization effects, as well as the impact of different types of wire rope core conveyor belts on the proposed quantitative damage identification method.

VI. Conclusion

This research focuses on the detection of internal damage in wire rope core conveyor belts, establishing an experimental platform to simulate realistic operating conditions. Aiming to quantitatively identify wire rope breakage, this study proposes a GWO-BP neural network method to address issues such as slow convergence and the propensity for local extrema in BP neural networks, significantly improving the accuracy of wire rope damage detection. The following conclusions can be drawn from the experimental results:

- a. With a training set of 500 groups and a test set of 200 groups, the BP neural network's prediction errors were predominantly concentrated in the range where the actual number of broken wires was 2, with six errors observed. Only two errors occurred in the range where the actual broken

wire count was 4, indicating relatively good recognition performance. The optimized BP neural network demonstrated a notable reduction in prediction errors, decreasing the overall error count from 18 to 9, thereby significantly enhancing accuracy.

- b. The quantitative identification range for wire rope breakage in this study spans 1–5 broken wires. For actual counts of 1 and 2, the BP neural network's recognition accuracy fell below 90%, while counts of 3, 4, and 5 yielded relatively higher accuracy. The GWO-BP neural network consistently outperformed the BP model under all tested conditions, achieving prediction accuracy rates of 95% and above.
- c. The GWO-BP neural network model achieved an average accuracy of 96.0%, with the optimized BP model's accuracy improving by 5.5% and the mean square error reducing from 0.041 to 0.028. This confirms the effectiveness of the algorithm. The GWO-BP neural network can swiftly and accurately detect instances of wire rope breakage, offering a novel non-destructive testing method for wire rope core conveyor belts and providing theoretical support for the development of such equipment by enterprises, demonstrating promising application prospects.

Acknowledgment

This research was supported by the National Natural Science Foundation of China (52465008); Basic Research Funds for Universities directly under the Inner Mongolia Autonomous Region (2024QNJS012; 2024YXXS020; 2023RCTD011). "The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results."

References

- [1] Paweł M. A Comprehensive Review of Steel Wire Rope Degradation Mechanisms and Recent Damage Detection Methods [J]. *Sustainability*, 2023, 15(6): 5441-5441.
- [2] Shiwei L, Yanhua S, Xiaoyuan J, et al. A Review of Wire Rope Detection Methods, Sensors and Signal Processing Techniques [J]. *Journal of Nondestructive Evaluation*, 2020, 39(4).
- [3] Xinyu L, Xianguo L, Mingwei S, et al. Quantitative analysis of bond and splice strength

of steel cord conveyor belt [J]. *Journal of Adhesion Science and Technology*, 2020, 34(14): 1544-1555.

[4] Zhou P, Zhou G, Zhu Z, et al. A Review of Non-Destructive Damage Detection Methods for Steel Wire Ropes [J]. *Applied Sciences*, 2019, 9(13).

[5] Xie Jin, Ren Wenqing. Detection System for Wire Rope Core Conveyor Belts in Coal Mines [J]. *Automation in Mining*, 2021, 47(S1): 69-71.

[6] Donglai Z, Enchao Z, Xiaolan Y. Quantitative Method for Detecting Internal and Surface Defects in Wire Rope [J]. *NDT & E International*, 2021, 119(prepublish): 102405.

[7] Zhou, Ping; Zhou, Gongbo¹, et al. Visual Sensing Inspection for the Surface Damage of Steel Wire Ropes With Object Detection Method [J]. *IEEE SENSORS JOURNAL*. 2022, Vol. 22 (No. 23): 22985-22993.

[8] Shiwei L, Yanhua S, Xiaoyuan J, et al. Comparison and analysis of multiple signal processing methods in steel wire rope defect detection by hall sensor [J]. *Measurement*, 2021, 171, 108768.

[9] Zhen S, Jianhua Y, F. A M S, et al. A novel adaptive moving average method for signal denoising in strong noise background [J]. *The European Physical Journal Plus*, 2021, 137(1).

[10] Wei G, Donglai Z, Xueli Z. Tension Monitoring and Defect Detection by Magnetostrictive Longitudinal Guided Wave for Fine Wire Rope [J]. *IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT*, 2021, 70.

[11] Zeng guang Z, Juwei Z. Quantitative Nondestructive Testing of Broken Wires for Wire Rope Based on Multi-Image Fusion [J]. *Russian Journal of Nondestructive Testing*, 2022, 58(7): 643-656.

[12] Shiwei L, Yanhua S, Xiaoyuan J, et al. A new MFL imaging and quantitative nondestructive evaluation method in wire rope defect detection [J]. *Mechanical Systems and Signal Processing*, 2022, 163.

[13] Mohamed, Hossam H, et al. Forecasting the Real Estate Housing Prices Using a Novel Deep Learning Machine Model [J]. *CIVIL ENGINEERING JOURNAL-TEHRAN*. 2023, Vol. 9(Special): 46-64.

[14] Setiawan, et al. Indoor Climate Prediction Using Attention-Based Sequence-to-Sequence Neural Network [J]. *CIVIL ENGINEERING JOURNAL-TEHRAN*. 2023, Vol. 9(No. 5): 1105-1120.

[15] Donglai Z, Enchao Z, Xiaolan Y. Quantitative Method for Detecting Internal and Surface Defects in Wire Rope [J]. *NDT & E International*, 2021, 119(prepublish): 102405.

[16] Jinyu G, Xinxin S, Yongdang C. Method for identifying the impact load condition of thin-walled

structure damage based on PSO-BP neural network. [J]. *Science progress*, 2022, 105(1).

[17] Zhigui D, Changyou W, Xisong F, et al. Research and Application of Back Propagation Neural Network-Based Linear Constrained Optimization Method [J]. *IEEE ACCESS*, 2021, 9126579-126594.

[18] Zhou, C, Wei, C, Wang, W. A New Detection Method Based on Magnetic Leakage Theory and BP Neural Network for Broken Steel Strands in ACSR Conductor. *IEEE Sens. J.* 2022, 22, 19620–19634.

[19] Qiang Y, Juwei Z, Quankun C. Quantitative detection of wire rope damage based on local structural characteristics [J]. *Journal of Intelligent & Fuzzy Systems*, 2023, 45(3): 4337-4347.

[20] Liancheng Dou, Weixia Zhan, Xiaorui Bai. Identification of Internal and External Wire Breakage Damage in Wire Ropes [J]. *Automation in Mining*, 2021, 47(03): 83-88.

[21] Yiqing Z, Zesen F, Sui S, et al. A quantitative identification method based on CWT and CNN for external and inner broken wires of steel wire ropes [J]. *Heliyon*, 2022, 8(11): e11623-e11623.

[22] Dong Wu, Baojin Zhang, Xianjun Sui, et al. Identification of Wire Rope Damage Based on Adaptive Shifted Average Denoising and BP Neural Network [J]. *Nondestructive Testing*, 2022, 44(08): 14-19.

[23] Shiwei L, Muchao C. Wire Rope Defect Recognition Method Based on MFL Signal Analysis and 1D-CNNs. [J]. *Sensors (Basel, Switzerland)*, 2023, 23(7).

[24] Yang Y, Zhan Z, Liu Y. A novel damage identification algorithm by combining the boundary element method and a series connection neural network [J]. *Engineering Applications of Artificial Intelligence*, 2024, 133(PA): 108010.

[25] Yonghua B, Minzhou L, Fenglin P. An Algorithm for Solving Robot Inverse Kinematics Based on FOA Optimized BP Neural Network [J]. *Applied Sciences*, 2021, 11(15): 7129-7129.

[26] Zenghua C, Lingjian Z, He L, et al. Research on bearing fault diagnosis based on improved genetic algorithm and BP neural network [J]. *Scientific Reports*, 2024, 14(1): 15527.

[27] Jinyu G, Xinxin S, Yongdang C. Method for identifying the impact load condition of thin-walled structure damage based on PSO-BP neural network. [J]. *Science progress*, 2022, 105(1): 368504221079184-368504221079184.

[28] Xin Z, Dexuan Z, Xin S. A Novel Simple Particle Swarm Optimization Algorithm for Global Optimization [J]. *Mathematics*, 2018, 6(12): 287-287.

- [29] Wenzhou Y. Forecast of agricultural water resources demand based on particle swarm algorithm[J].Acta Agriculturae Scandinavica, Section B — Soil & Plant Science, 2022, 72(1): 30-42.
- [30] Liu, Yunyun, As'arry, et al. Review of the grey wolf optimization algorithm: variants and applications.[J].Neural Computing & Applications. 2023, Vol. 36(No. 6): 1-23.
- [31] Xiaofeng Zhang, Xiuying Wang. A Review of Grey Wolf Optimization Algorithm Research [J]. Computer Science, 2019, 46(03): 30-38.
- [32] Haojie Zhang, Jiaxing Chen,et al. Grey Wolf Optimization Algorithm Based on Follow-Controlled Learning Strategy [J]. IEEE Access. 2023:1.
- [33] Zhang, L, Wang, FL, et al. A constrained optimization method based on BP neural network[J].Neural Computing and Applications. 2018, Vol. 29(No. 2): 413-421.
- [34] Meixian Wu, Dongli Zhang. A Review of Improvements to BP Neural Networks and Their Applications in Nondestructive Testing [J]. China Testing, 2023, 49(S2): 1-6.
- [35] Shaohui S, Xingyu X, Xin W, et al. Modeling the SOFC by BP neural network algorithm[J]. International Journal of Hydrogen Energy, 2021, 46(38): 20065-20077.
- [36] Zhiwei Zhao, Ben Zhao, Chao Ge, et al. Parameter Tuning of Quadrotor UAVs Based on GWO-PSO Algorithm [J]. Firepower and Command Control, 2024, 49(06): 135-140.
- [37] Náfate C M, Mendoza C A, Salgado V C, et al. Optimizing Lithium-Ion Battery Modeling: A Comparative Analysis of PSO and GWO Algorithms [J]. Energies, 2024, 17(4).
- [38] Pan, Chengsheng, Si, et al. A four-step decision-making grey wolf optimization algorithm [J]. Soft Computing, 2021, 25(22): 1-17.
- [39] Yuxiang H, Huanbing G, Zijian W, et al. Improved Grey Wolf Optimization Algorithm and Application [J]. Sensors, 2022, 22(10):3810-3810.