frontiers | Frontiers in Mechanical Engineering

TYPE Original Research
PUBLISHED 07 February 2025
DOI 10.3389/fmech.2024.1496377

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RECEIVED 14 September 2024
ACCEPTED 23 December 2024
PUBLISHED 07 February 2025

CITATION
Lu Z, He P, Liu H, Li J and Lu Z (2025) A GA-BP neural network algorithm for fault detection of transmission tower bolts.
Front. Mech. Eng. 10:1496377.
doi: 10.3389/fmech.2024.1496377

A GA-BP neural network algorithm for fault detection of transmission tower bolts

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Background: In the power system, the identification of the health status of the transmission tower is a daily task that must be performed. In addition, bolt loosening is a common damage mode affecting the main materials of transmission towers. When bolt loosening occurs, it weakens the bearing capacity of the transmission tower. If not detected and addressed in a timely manner, serious adverse events, such as tower collapse, may occur which will endanger the normal operation of the power system.

Methods: Based on this, in order to ensure the normal operation of the transmission tower and improve the identification effect of bolt loosening, the GP-BP neural network algorithm was applied to the detection process. The feasibility of this algorithm was evaluated through the quantitative analysis of different damage degrees.

Result: The results are as follows: 1) except for the average accuracy rate of substructure 7, which is 89.74%, the identification accuracy of other substructures is more than 90%, indicating that the GA-BP neural network algorithm is effective in identifying the single-damage degree of the tower bolt loosening in the main material; 2) the identification accuracy of double-damage substructure is also more than 90%, indicating that the GA-BP algorithm is effective in identifying the double-damage degree of the tower bolt loosening in the main material.

Conclusion: In summary, it can be concluded that both the single- and double-damage degree conditions exhibit a relatively considerable recognition accuracy. In addition, the recognition effect of the algorithm under the double-damage degree condition is better than that of the single-damage degree condition. Therefore, it can be applied in practical projects involving double-damage degree conditions to improve the recognition effect of bolt-loosening faults and provide reliable technical support for the safe operation of transmission equipment.

KEYWORDS

GA-BP neural network algorithm, bolt-loosening failure, detection, power transmission and inspection, electrical automation

Introduction

A transmission tower is a crucial part of the power system, and the bolt serves as a key connection element in the tower structure. Faults in these bolts can inhibit the normal operation of the equipment and hence affect the safety of the transmission line (Lu et al., 2024; Wang et al., 2023; Tian et al., 2022; Jiang et al., 2021). For the fault detection of tower bolts, traditional methods often rely on manual inspection or regular maintenance, which has low efficiency and high cost. The GA-BP neural network algorithm is an avant-garde algorithm with excellent generalization ability in fault detection (Yang and Li, 2023). Combined with the GP-BP neural network algorithm and optimization strategy, the abnormal state of tower bolts can be identified more accurately and quickly, and the fault detection efficiency and accuracy of equipment can be improved (Li et al., 2023). Therefore, the detection of bolt-loosening faults in transmission towers using this algorithm has positive practical significance and value for the power transmission industry.

In order to improve the accuracy of detecting transmission tower bolt-loosening faults, two domestic scholars, Wan Shuting and Sun Ruibin, proposed a fusion detection algorithm. Using this fusion algorithm, a sensitivity analysis of local measurement points on the tower was carried out, and it was found that the loosening of transmission tower bolts could be detected with the fusion algorithm, which has a relatively considerable detection effect. It has contributed to the development of local bolt-loosening detection of towers (Wan et al., 2023). In the same year, to avoid interfering with the operation of transmission towers, Liu Jie, Wang Xiangdong, and other scholars conducted targeted research on bolt-loosening faults and proposed a fault detection method based on wavelet energy in general. Vibration signals before and after bolt loosening were obtained through pulse excitation, and then the obtained original data were decomposed by a wavelet to find out the energy spectrum of each frequency band. The loosening of bolts is determined by comparing the change law between the two sections of tower materials, which aids in the detection of bolt faults (Liu et al., 2023). With the aim of not affecting the normal operation of transmission towers, Liu Guanghui and Wu Chuan et al., conducted quantitative empirical research on the bolt fastening characteristics of transmission towers and found that the residual preload of the bolt is in inverse proportion to the vibration amplitude; after increasing the vibration amplitude, it will decrease, but it is difficult to use vibration frequency to affect the dynamic characteristics of transmission tower bolts. At the same time, after the lubrication intervention, it is found that the residual preload of the bolt surface is reduced, indicating that, in practice, when the preload of the bolt is determined to be too high, the lubrication operation can be used to intervene. In addition, it is found that the loosening probability and data discreteness are inversely related to the initial preload and decrease with an increase in the initial preload. This study provides a basis for detecting bolt-loosening faults and has a positive promoting effect (Liu et al., 2022). In order to solve this problem, an adaptive clustering weighting algorithm is used to mitigate the problem of oversampling and improve the effect of fault diagnosis (Li et al., 2024). In order to solve the problem of abnormal vibration data, AI designed a multi-layer perceptron, which can effectively detect the problem of abnormal vibration data and provide convenience for such data processing (Fan et al., 2024). It is not difficult to find that many domestic scholars have joined the research on the loosening of transmission tower bolts and have achieved certain results. However, in essence, this kind of research is one-way, cannot be used in other bolt-loosening problem monitoring conditions, and has certain limitations.

In this paper, the GP-BP neural network algorithm is a fusion algorithm that can deal with bolt loosening under different conditions, such as single- and double-damage conditions, and will not be constrained by conditions. Therefore, this algorithm will be used to detect faults in transmission tower bolts. The feasibility of this method is tested empirically, and the final result can capture the bolt-loosening fault through this more comprehensive detection method to ensure the normal operation of the transmission tower.

Transmission tower bolt loose fault detection method

Overview of the genetic algorithm

The genetic algorithm is a type of random optimization search method (Tang et al., 2019). It finds the optimal solution by simulating the natural evolution process. Its main feature is its ability to directly manipulate structural objects without being limited by derivation and functional continuity. It also has inherent implicit parallelism and high global optimization capability. By using probability optimization methods, the optimized search space can be automatically obtained without the need for certain rule guidance, and the search direction can be adaptively adjusted. Due to the fact that the overall search strategy and optimization search methods of genetic algorithms do not rely on gradient information or other auxiliary knowledge, only the objective function and corresponding fitness function that affect the search direction are needed, providing a universal framework for solving complex system problems. It is not dependent on the specific domain of the problem and is, therefore, widely used in combinatorial optimization. Machine learning, signal processing, and adaptive control are key technologies in modern intelligent computing.

Basic steps of the genetic algorithm

It is not difficult to find through the analysis of genetic algorithms that their genetic operations can be divided into three modes: first, selection; second, crossover; and third, mutation. Under this optimal choice, the optimal solution is determined. The specific process is shown in Figure 1.

Design of the BP neural network based on genetic algorithm optimization

In the damage identification process, if the BP neural network is used alone, there is a high possibility of unfriendly convergence (Xie et al., 2023). Since the network structure and number of hidden layer neurons simultaneously calculate the threshold and weight of the algorithm through trial calculation, scholars will add other algorithms to intervene in order to improve the generalization ability of the BP neural network algorithm, and the genetic algorithm is particularly suitable for optimization problems with only coding concepts; in general, it is used to adjust the threshold

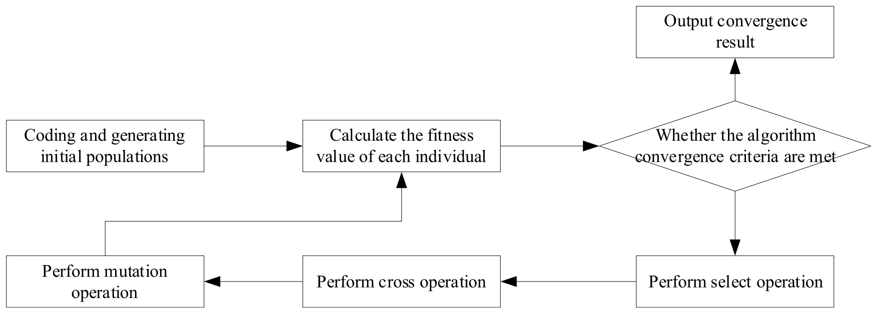

FIGURE 1
Genetic algorithm flow.

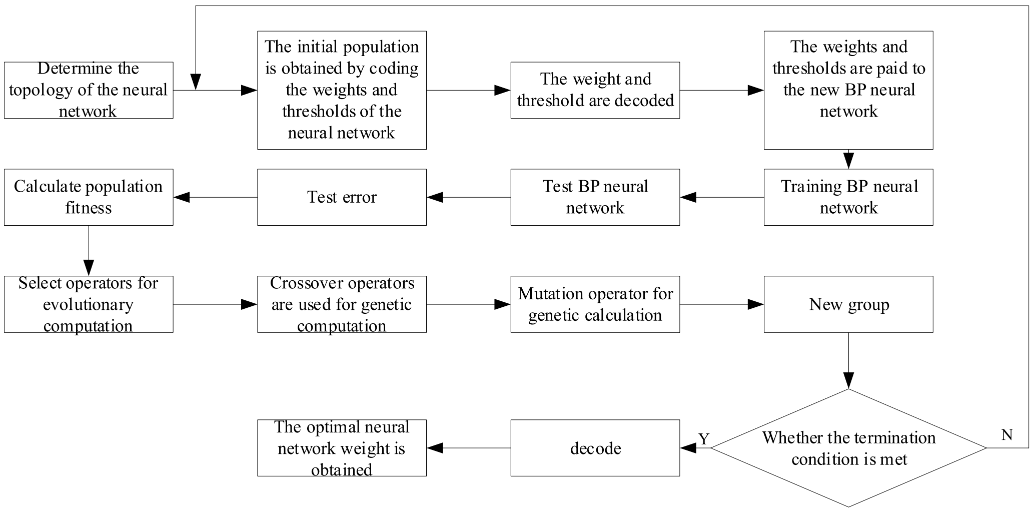

FIGURE 2
Process of optimizing the BP neural network using the genetic algorithm.

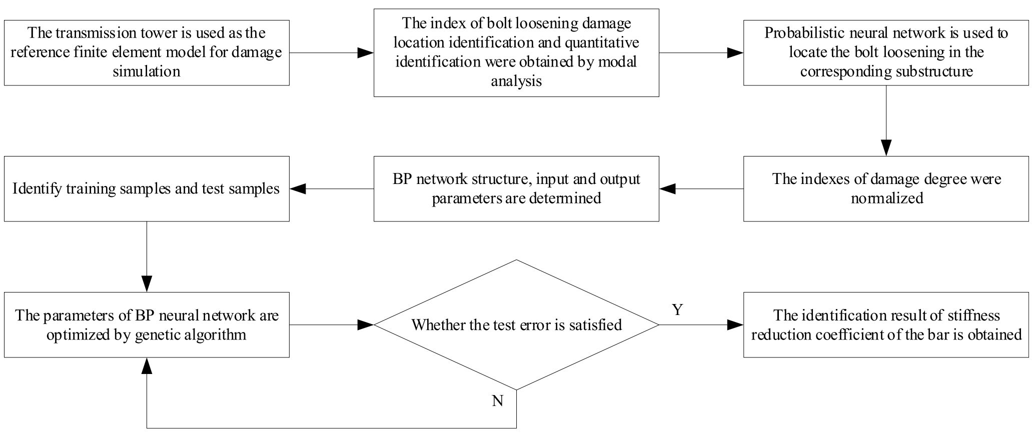

FIGURE 3
Identification process.

TABLE 1 Main rod numbers of substructures 1–9.

Substructural region	Member number	Number of rods
Substructure 1	1, 4, 7, and 10	4
Substructure 2	13, 14, 17, 18, 21, 22, 25, and 26	8
Substructure 4	15, 16, 19, 20, 23, 24, 27, 28, 62, 63, 64, and 65	12
Substructure 4	70, 71, 72, 73, 66, 67, 68, and 69	8
Substructure 5	74, 75, 76, 77, 78, 79, 80, and 81	8
Substructure 6	300, 301, 303, 304, 309, 311, 326, 327, 329, 330, 331, 335, 337, 352, 353, 355, 356, 358, 359, 360, 361, 363, 78, 379, 381, 382, 383, 384, 387, and 389	31
Substructure 7	451, 453, 454, 456, 457, 459, 460, 461, 462, 463, 466, 465, 466, 467, 469, 470, 471, 472, 473, 474, 476, 477, 478, 479, 480, 481, 482, 483, 484, 486, 487, 488, 489, and 490	31
Substructure 8	451, 452, 453, 454, 455, 456, 457, 459, 460, 461, 462, 463, 464, 465, 466, 467, 469, 470, 471, 472, 473, 474, 476, 477, 478, 479, 480, 481, 482, 483, 484, 486, 487, 488, 489, and 490	36
Substructure 9	493, 498, 500, 502, 503, 506, 507, 510, 511, 512, 516, 517, 520, 521, 524, and 525	16

TABLE 2 Quantitative identification results of single damage of substructure 1 member.

Damaged member number	Damage degree	Theoretical output	Actual output	Relative error
1	85%	0.85	0.8266	2.23%
	75%	0.75	0.7319	1.81%
	65%	0.65	0.6437	0.63%
	55%	0.55	0.5456	0.44%
	45%	0.45	0.4410	0.90%
4	85%	0.85	0.8533	0.33%
	75%	0.75	0.7525	0.25%
	65%	0.65	0.6539	0.30%
	55%	0.55	0.5517	0.17%
	45%	0.45	0.4596	0.96%
7	85%	0.85	0.8597	0.97%
	75%	0.75	0.7614	1.14%
	65%	0.65	0.6628	1.28%
	55%	0.55	0.5647	1.47%
	45%	0.45	0.4585	0.85%
10	85%	0.85	0.8566	0.66%
	75%	0.75	0.7548	0.48%
	65%	0.65	0.6522	0.22%
	55%	0.55	0.5519	0.19%
	45%	0.45	0.4596	0.96%

and weight of the algorithm (Yang and Li, 2023). It is also applied to structural damage identification. Genetic algorithms encode the parameters, not the parameters themselves. At the same time, the optimal solution is obtained through a group search. Genetic algorithms are different. The selection, crossover, and mutation of the algorithms are carried out in a probabilistic manner, rather than using a completely random blind search. The shortcomings of the BP algorithm are addressed. In order to comprehensively analyze the integration of genetic and BP algorithms, three levels are analyzed: first, the structure of the BP algorithm is determined;

TABLE 3 Quantitative identification results of single damage of substructure 2 member.

Damaged member number	Damage degree	Theoretical output	Actual output	Relative error
13	85%	0.85	0.8482	0.2%
	75%	0.75	0.7421	0.79%
	65%	0.65	0.6366	1.34%
	55%	0.55	0.5543	0.43%
	45%	0.45	0.4745	2.45%
14	85%	0.85	0.8441	0.59%
	75%	0.75	0.7559	0.59%
	65%	0.65	0.6555	0.55%
	55%	0.55	0.5494	0.06%
	45%	0.45	0.4566	0.66%
17	85%	0.85	0.8334	1.66%
	75%	0.75	0.7419	0.81%
	65%	0.65	0.6548	0.48%
	55%	0.55	0.5708	2.08%
	45%	0.45	0.4859	3.59%
18	85%	0.85	0.8499	0.01%
	75%	0.75	0.7471	0.29%
	65%	0.65	0.6462	0.38%
	55%	0.55	0.5501	0.01%
	45%	0.45	0.4722	2.22%
21	85%	0.85	0.8441	0.59%
	75%	0.75	0.7516	0.16%
	65%	0.65	0.6516	0.16%
	55%	0.55	0.5577	0.77%
	45%	0.45	0.4766	2.66%
22	85%	0.85	0.8511	0.11%
	75%	0.75	0.7580	0.8%
	65%	0.65	0.6694	1.94%
	55%	0.55	0.5788	2.88%
	45%	0.45	0.4985	4.85%
25	85%	0.85	0.8563	0.63%
	75%	0.75	0.7541	0.41%
	65%	0.65	0.6402	0.98%
	55%	0.55	0.5399	1.01%
	45%	0.45	0.4704	2.04%
26	85%	0.85	0.8355	1.45%
	75%	0.75	0.7499	0.01%
	65%	0.65	0.6548	0.48%

(Continued on following page)

TABLE 3 (*Continued*) Quantitative identification results of single damage of substructure 2 member.

Damaged member number	Damage degree	Theoretical output	Actual output	Relative error
	55%	0.55	0.5477	0.23%
	45%	0.45	0.4605	1.05%

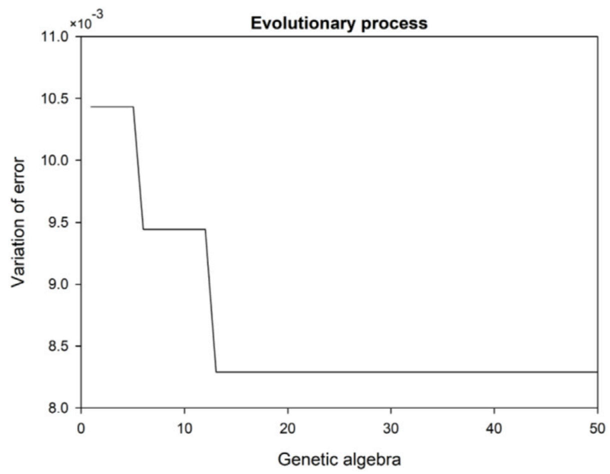

FIGURE 4
Convergence results of substructure 1 damage quantitative identification.

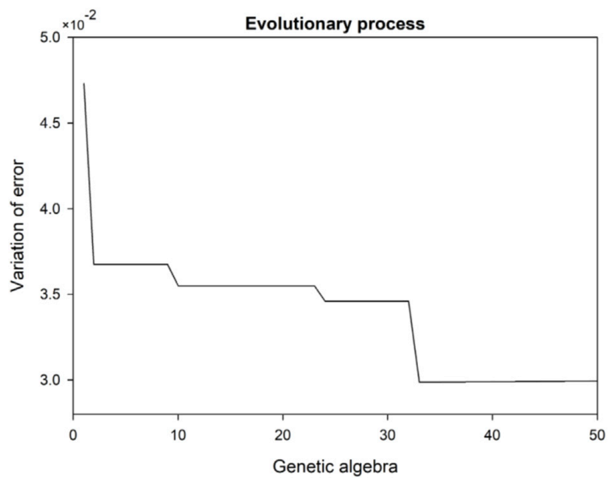

FIGURE 5
Convergence results of substructure 2 damage quantitative identification.

second, the fusion of the genetic algorithm is analyzed; and third, the prediction of the BP algorithm is made. Among them, under the influence of the fitting function, the number of partial parameters is obtained, and based on this, the individual length of the genetic algorithm is implemented. The individual fitness value is calculated using the fitness function. Through selection, crossover, and mutation operations, the genetic algorithm can find the optimal adaptive value of the corresponding individual. Under the influence of the genetic algorithm, the optimal individual is obtained, then the threshold and weight are scheduled, and the final prediction function is obtained through training. The specific process of optimizing the BP algorithm through this algorithm is shown in Figure 2.

Parameter selection and detection process

Natural frequency change rate

When the structure is damaged, the variable $\Delta\omega_i$ of the ith-order frequency is related to the change ΔK in K of the structure stiffness matrix and the damage position parameter r. The formula is as follows Formula 1:

$$\Delta\omega_i = f_i(\Delta K, r). \tag{1}$$

Using the series expansion and ignoring the highest term, we can obtain Formula 2

$$\Delta\omega_i = \Delta K g_i(r). \tag{2}$$

Assuming that no mass loss occurs in the structure and that the second-order term is ignored, the vibration mode of the structure is shown in Formula 3:

$$\Delta\omega_i^2 = \frac{\phi_i^T \Delta K \phi_i}{\phi_i^T \Delta M \phi_i}. \tag{3}$$

The overall stiffness matrix of the structure is decomposed into several element stiffness matrices, and the variable form of the element can be obtained Formula 4:

$$\varepsilon_m(\phi) = f(\phi), \tag{4}$$

where ε_m represents unit deformation and m indicates the unit number. Further derivation leads to Formula 5:

$$\phi_i^T \Delta K \phi_i = \sum_{m-1}^{M} \varepsilon_m^T(\phi_i)\Delta k_m \varepsilon_m(\phi_i), \tag{5}$$

where M represents the total number of units. For a single damaged unit, it can be calculated using Formula 6.

$$\Delta\omega_i^2 = \frac{\varepsilon_N^T(\phi_i)\Delta k_N \varepsilon_N(\phi_i)}{\phi_i^T M \phi_i}. \tag{6}$$

At this time, let $\Delta k_N = \alpha_N K_N$ because different elements have different influences on the structural stiffness. $\alpha_N = \frac{\Delta k_N}{K_N}$ is a matrix form, and by substituting Formula 6, we can obtain Formula 7

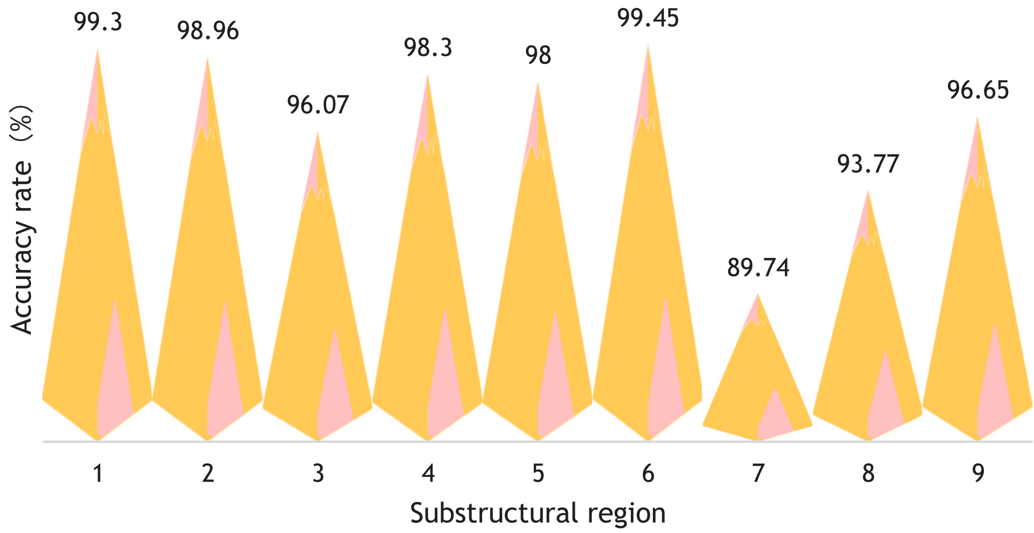

FIGURE 6
Recognition accuracy of different substructure regions.

$$\Delta\omega_i^2 = \frac{\alpha_N \varepsilon_N^T(\phi_i) k_N \varepsilon_N(\phi_i)}{\phi_i^T M \phi_i}. \tag{7}$$

By substituting the vibration equation, we can obtain Formula 8

$$[(K + \Delta K) - (\omega^2 + \Delta\omega^2)(M + \Delta M)](\phi + \Delta\phi) = 0. \tag{8}$$

Finally, integration yields the damage identification equation for the frequency change rate Formula 9:

$$\mathrm{FCR}_i = \frac{\Delta\omega_i}{\omega_i} = \sqrt{\frac{\phi_i^T \Delta K \phi_i}{\phi_i^T K \phi_i}} = \sqrt{\frac{\alpha_N \varepsilon_N^T(\phi_i) K_N \varepsilon_N(\phi_i)}{\phi_i^T K \phi_i}}. \tag{9}$$

It can be observed that when the damage location is determined in the damage identification process, the frequency change rate can be used as a judgment indicator. Therefore, the frequency change rate will be used as the indicator of bolt-loosening failure to carry out damage identification.

Identification process

The basis for the quantitative identification of bolt-loosening damage through the GA-BP neural network is to first locate the damage within the substructure and then identify the degree of damage to the main material members within the substructure where bolt-loosening damage occurs. The flow diagram is shown in Figure 3.

Result analysis

GA-BP neural network sample settings

In this paper, the GA-BP neural network is simulated by the numerical method, with the main material damage occurring in the same substructure as a case example.

The quantitative method of bolt-loosening damage is verified, and the optimal substructure for bolt-loosening damage on the main steel tower is divided into nine substructure divisions, referred to as substructure models. Therefore, the main steel in the same substructure within substructure model I is taken as the research object, and the main rod numbers of substructures 1 to 9 are shown in Table 1.

Fault detection results under single-damage loosening conditions

Through fault detection under single-damage loosening conditions, the quantitative identification results for single-damage conditions in substructures 1 and 2 were obtained, as shown in Tables 2, 3, respectively. The convergence of the damage quantitative identification for substructures 1 and 2 is shown in Figures 4, 5, respectively. After continuous debugging, it was determined that the optimal number of intermediate neurons for substructure 1 is set to 8, and for substructure 2, it is set to 11.

According to the results displayed in Figure 4, the minimum error value of the member in substructure 1 is achieved when the genetic algebra is 13. According to Table 2, the maximum relative error value of the member in substructure 1 is 2.24%, and the relative error value of all the members in the working condition is less than 5%. According to Figure 5, the minimum error value of the member in structure 2 is achieved when the genetic algebra is 33. According to Table 3, the maximum relative error value of substructure 2 is 4.85%, and the relative error value of all the members and working conditions is also within 5%. It shows that the GA-BP neural network algorithm can effectively identify the damage degree of the members of substructures 1 and 2. In order

TABLE 4 Fault detection results of substructure 1 under both damage and loosening conditions.

Damaged member number	Damage degree	Theoretical output	Actual output	Relative error
1 and 7	85%	0.85	0.8548	0.48%
	75%	0.75	0.7517	0.17%
	65%	0.65	0.6517	0.17%
	55%	0.55	0.5529	0.29%
	45%	0.45	0.4624	1.24%
4 and 10	85%	0.85	0.8566	0.66%
	75%	0.75	0.7539	0.39%
	65%	0.65	0.6533	0.33%
	55%	0.55	0.5536	0.36%
	45%	0.45	0.4613	1.13%
1 and 10	85%	0.85	0.8593	0.93%
	75%	0.75	0.7554	0.54%
	65%	0.65	0.6562	0.62%
	55%	0.55	0.5571	0.71%
	45%	0.45	0.4668	1.68%
4 and 7	85%	0.85	0.8576	0.76%
	75%	0.75	0.7528	0.28%
	65%	0.65	0.6527	0.27%
	55%	0.55	0.5533	0.33%
	45%	0.45	0.4642	1.42%
1 and 4	85%	0.85	0.8522	0.22%
	75%	0.75	0.7521	0.21%
	65%	0.65	0.6533	0.33%
	55%	0.55	0.5544	0.44%
	45%	0.45	0.4646	1.46%
7 and 10	85%	0.85	0.8477	0.23%
	75%	0.75	0.7514	0.14%
	65%	0.65	0.6548	0.48%
	55%	0.55	0.5561	0.61%
	45%	0.45	0.4658	1.58%

to better discuss the applicability of the GA-BP neural network algorithm in identifying single-damage degrees, the identification accuracy of different substructure regions was tested, as shown in Figure 6.

It can be observed that, except for substructure 7, which has an average accuracy of 89.74%, the recognition performance of the remaining substructures exceeds 90%, indicating that the GA-BP algorithm is effective in identifying the degree of single damage to the loose main materials of iron tower bolts. Substructures 1 to 6 represent the average accuracy of single-damage identification for the main material of the tower body, while substructures 7 to 9 represent the average accuracy of single-damage identification for the main material of the tower head. Moreover, the average accuracy of single-damage identification for the main material of the tower body is higher than that for the tower head, indicating that the single-damage identification indicators obtained when the main material of the tower body is damaged are more sensitive

TABLE 5 Fault detection results of substructure 2 under both damage and loosening conditions.

Damaged member number	Damage degree	Theoretical output	Actual output	Relative error
13 and 21	85%	0.85	0.8487	0.13%
	75%	0.75	0.7508	0.08%
	65%	0.65	0.6477	0.23%
	55%	0.55	0.5514	0.14%
	45%	0.45	0.4638	1.38%
14 and 22	85%	0.85	0.8485	0.15%
	75%	0.75	0.7512	0.12%
	65%	0.65	0.6516	0.16%
	55%	0.55	0.5528	0.28%
	45%	0.45	0.4531	0.31%
17 and 25	85%	0.85	0.8471	0.29%
	75%	0.75	0.7471	0.29%
	65%	0.65	0.6364	1.36%
	55%	0.55	0.5392	1.08%
	45%	0.45	0.4531	0.31%
18 and 26	85%	0.85	0.8522	0.22%
	75%	0.75	0.7523	0.23%
	65%	0.65	0.6538	0.38%
	55%	0.55	0.5521	0.21%
	45%	0.45	0.4510	0.10%
13 and 17	85%	0.85	0.8452	0.48%
	75%	0.75	0.7529	0.29%
	65%	0.65	0.6419	0.81%
	55%	0.55	0.5544	0.44%
	45%	0.45	0.4686	1.86%
21 and 25	85%	0.85	0.8466	0.34%
	75%	0.75	0.7527	0.27%
	65%	0.65	0.6519	0.19%
	55%	0.55	0.5543	0.43%
	45%	0.45	0.4685	1.85%
25 and 13	85%	0.85	0.8489	0.11%
	75%	0.75	0.7542	0.42%
	65%	0.65	0.6536	0.36%
	55%	0.55	0.5556	0.56%
	45%	0.45	0.4655	1.55%
21 and 17	85%	0.85	0.8432	0.68%
	75%	0.75	0.7518	0.18%
	65%	0.65	0.6496	0.04%

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TABLE 5 (*Continued*) Fault detection results of substructure 2 under both damage and loosening conditions.

Damaged member number	Damage degree	Theoretical output	Actual output	Relative error
	55%	0.55	0.5481	0.19%
	45%	0.45	0.4599	0.99%

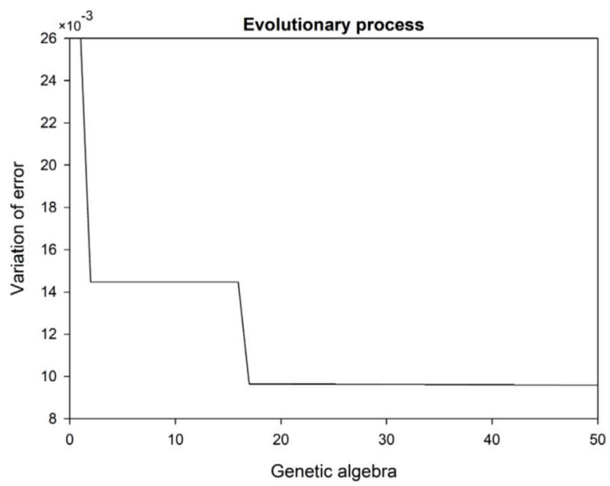

FIGURE 7
Identification convergence results of sub-structure 1 under double damage and loosening conditions.

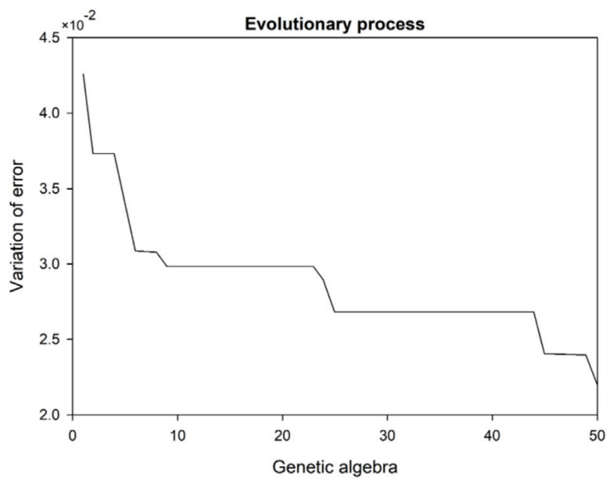

FIGURE 8
Identification convergence results of sub-structure 2 under double damage and loosening conditions.

than those obtained when the main material of the tower head is damaged.

Fault detection results under double damage and loosening conditions

Taking substructures 1 and 2 as examples, the double-damage conditions were quantitatively identified, and the results are shown in Tables 4, 5. The resulting convergence is shown in Figures 7, 8. After continuous debugging, it is determined that the optimal number of interneurons in substructure 1 is set to 9, and the optimal number of interneurons in substructure 2 is set to 10.

Figure 7 shows that the double-damaged member in substructure 1 achieves the minimum error when the genetic algebra is 16. Table 4 shows that the maximum relative error is 1.68% when nos 1 and 10 members are damaged at the same time in substructure 1, and the relative error values of all members are within 5% under working conditions. Figure 8 shows that the double-damaged member in structure 2 has reached the minimum error when the genetic algebra is 50. Table 5 shows that in substructure 2, when the member nos 21 and 25 are damaged at the same time, the maximum relative error is 1.86%, and the relative error values of all the members and working conditions are within 5%. It shows that the GA-BP neural network algorithm can effectively identify the damage degree of the members of substructures 1 and 2. In order to better discuss the applicability of the GA-BP neural network algorithm in dual damage degree recognition, the comparison diagram of recognition accuracy in different substructure regions is shown in Figure 9.

Figure 9 shows that the recognition effect of double-damage substructure has exceeded 90%. Among them, the lowest recognition accuracy rate is 91.3%, while the highest is 99.56%; the recognition accuracy rate of other substructure regions fluctuates at approximately 95%, and the recognition accuracy is relatively stable, indicating that the GA-BP algorithm is effective in identifying the double-damage degree of the tower bolt loosening. In the double-damage degree identification, the average accuracy of tower body identification is higher than that of tower head identification, indicating that the double-damage identification index is more sensitive to damage in the tower body than that in the tower head. Compared with the results of the damage recognition degree of the single-damage model, it can be observed that when the double damage occurs in the tower member, the recognition accuracy is higher than that of the single damage of the tower member on the whole, indicating that the double-damage index is more sensitive and consistent with the actual engineering law.

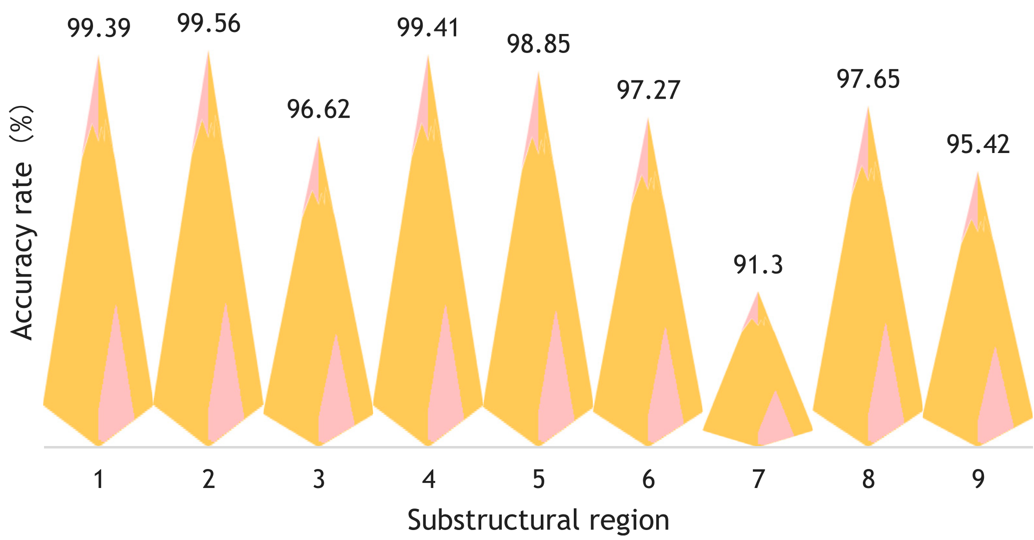

FIGURE 9
Recognition accuracy of different substructure regions.

Conclusion

On the basis of locating loosening damage in the main bolt of the tower, a quantitative identification method for bolt-loosening damage is proposed using the GA-BP neural network algorithm. Specifically, the quantitative damage identification of different substructures under single- and double-damage conditions is carried out, confirming the feasibility of the algorithm. The work and conclusions obtained are as follows: 1) in this work, the change rate of the whole tower's natural frequency is taken as the damage index, and the GA-BP neural network algorithm is used to quantitatively identify the loosening damage of the main bolt of the tower. 2) Single- and double-damage conditions are set for the main rods in different substructures, and training using the GA-BP neural network algorithm is used to effectively identify the damage degree of the damaged members. 3) Under single-damage conditions, the average accuracy rate of the quantitative damage identification of the main rod in substructure 7 is 89.7%, and the average accuracy rate for the remaining substructures exceeds 90%; under double-damage conditions, the average accuracy rate of the quantitative damage identification of all the substructure rods exceeds 90%. It shows that the GA-BP neural network algorithm is effective in identifying single- and double-damage conditions. Due to the conclusion regarding the tower head, the identification effect of tower body damage has been obtained. On the whole, the research method proposed in this paper can cope with bolt fault identification under different damage conditions. However, due to limitations in knowledge, experience, and time, other material damage identification methods, such as for transverse partition, pole and tower inclines, and auxiliary materials, have not been examined nor compared with the most recent damage identification methods. In the future, we will focus on these aspects to gradually fill the research gap and improve the identification quality of each component of the tower.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material; further inquiries can be directed to the corresponding author.

Author contributions

ZqL: Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing, Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources. PH: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. HL: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. JL: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. ZyL: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This study was supported by the State Grid Shanxi Electric Power Company Technology Project: Research and Application of an Online Monitoring System for Bolt Looseness in Transmission Towers Based on DSP Voiceprint

Information (52051K240001). The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article, or the decision to submit it for publication.

Conflict of interest

Authors ZqL, PH, HL, JL, and ZyL were employed by the State Grid UHV Transmission Co. of SEPC.

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