Postprint of a neural network prediction study on the stresses of large-scale flange bolt groups based on finite element simulation

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Abstract

Stress monitoring of large-scale flange-connection bolt groups is an important requirement for ensuring the healthy operation of large equipment such as wind turbines. In this study, finite element simulation results of the stress in pretightened flange-connection bolts under varying external flange loads are used as data samples, and BP, GA-BP, and PSO-BP neural network models are employed to predict and analyze the stress of the bolt group. The results indicate that, when relative error is used as the evaluation criterion, the prediction accuracy of all three models decreases with the reduction of the minimum bolt stress in the bolt group and the increase of the maximum stress difference among bolts in the group; the prediction accuracy is higher when the bolt group is in the elastic stage than after some bolts have entered the plastic stage; GA-BP and PSO-BP exhibit higher prediction accuracy than BP, with PSO-BP achieving the highest accuracy. For bolts at higher stress levels (above 400 MPa), which are of greater concern, all three models yield relatively high prediction accuracy, with overall average errors below 2%.

Full Text

Stress Neural Network Prediction for Large-Scale Flange Bolt Groups Based on Finite Element Simulation

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Abstract

Stress monitoring of large-scale flange connection bolt groups is a critical requirement for the healthy operation of major equipment such as wind turbines. This study employs neural network models to predict and analyze the stress in bolt groups using finite element simulation results of pretensioned flange connection bolts under varying external flange loads as data samples. The results indicate that, when using relative error as the evaluation criterion, the prediction accuracy of all three models decreases with the reduction of the minimum bolt stress value in the bolt group and increases with the maximum stress difference among bolts. The prediction accuracy is higher when the bolt group is in the elastic stage compared to cases where some bolts have entered the plastic stage. Among the three models, GA-BP and PSO-BP demonstrate higher prediction accuracy, with PSO-BP achieving the highest precision. For high-stress bolts (above 400 MPa) that warrant greater attention, all three models achieve relatively high prediction accuracy, with overall average errors below 5%.

Keywords: flange connection bolts; bolt stress; finite element analysis; neural network prediction

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1. Introduction

Bolted flange connections represent an important mechanical joining method in component pre-assembly and structural installation, used to ensure proper sealing or connectivity. Damage or failure of flange connection bolts can compromise the safety of the entire connection system. Monitoring and analyzing the stress variation patterns and characteristics of flange bolt groups during operation is therefore significant for equipment safety [1-2].

In recent years, bolt stress detection technologies have made substantial progress [3-7], including but not limited to torque wrench methods, resistance strain gauge techniques, fiber Bragg grating methods, and ultrasonic force measurement. However, as equipment size increases, large-scale connection structures require more bolts to ensure connection strength, and large equipment typically faces more complex and variable operating environments. This presents enormous technical and economic challenges for stress monitoring of large-scale flange connection bolt groups. For instance, wind turbine installations are typically in remote locations with numerous flange connection bolts, making it impractical to monitor every bolt. Research on predicting the stress of the entire bolt group based on stress monitoring of a limited number of bolts is therefore of great significance.

This study, set against the backdrop of wind turbine systems, employs artificial neural network prediction methods to predict the stress condition of the entire bolt group using a limited number of bolt stress monitoring data. Previous research on mechanical-related neural network prediction for wind turbines has

Figure 1

Figure 1: Figure 1

achieved certain results. Zhou et al. [8] used SCADA data to establish a relationship model between wind turbine SCADA data and loads at key locations, with prediction results showing good consistency with measured data. Shao et al. [9] proposed a tower stress early warning method based on the Pearson coefficient method combined with grey neural networks, effectively predicting tower stress. Xue et al. [10] optimized neural networks using genetic algorithms and particle swarm algorithms to establish tower stress prediction models. Mao et al. [11] established an extended finite element method (XFEM) crack inversion analysis model, using displacement data from monitoring points obtained through forward analysis to train neural networks for crack identification. Tang et al. [12] proposed a machine learning method based on neural networks to predict the natural frequency of wind turbine tower structures with high accuracy. Additionally, Liu et al. [13] addressed the need for real-time monitoring of fuselage section stress changes before aircraft assembly, proposing a PSO-BiLSTM neural network-based method that not only provided more accurate predictions but also improved training efficiency.

Despite these advances, neural networks suffer from slow learning convergence and local minima issues [14], and research on stress prediction specifically for flange connection bolt groups remains limited. This study investigates a large-scale internally bolted flange connection, first conducting finite element analysis of bolt stresses under complex loading conditions to obtain stress data for large-scale connection bolt groups under various working conditions. Based on this data, neural network models are established to predict the overall stress of flange bolt groups using partial bolt stresses as inputs. The prediction performance of three models—BP, GA-BP, and PSO-BP—is compared and analyzed, providing theoretical and technical support for effectively solving the monitoring challenges of large-scale flange connection bolt groups in major equipment such as wind turbines.

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2. Finite Element Simulation Model

A large-scale bolted flange connection serves as the research object. The finite element model is shown in

. The model consists of upper and lower flange segments with identical dimensions, connected by 36 uniformly distributed circumferential bolts. Following established methods for similar problems [15-18] and to ensure computational efficiency while maintaining accuracy, each bolt' s shank and nut are simplified as a single unit, with thread and chamfer details omitted, and hex bolt heads simplified to circular heads [19].

Both flange segments and bolts use C3D8R elements in the finite element analysis. Material parameters are listed in Table 1. The flange and bolt material is 42CrMo. Hard contact is adopted between bolt heads and flanges as well as between flange surfaces, with Coulomb friction applied and a friction coefficient of 0.15.

Table 1. Material parameters in finite element analysis

Material	Young’ s Modulus (GPa)	Poisson’ s Ratio	Yield Strength (MPa)
42CrMo	210	0.3	940

Full constraints are applied to the bottom surface of the lower flange, and a pretension force of 155 kN is applied to each bolt. A lateral force load perpendicular to the flange axis is applied at a coupling point on the top surface of the upper flange. The stress in the flange connection bolt group varies with the magnitude and direction of this lateral force.

The finite element analysis consists of 150 steps. The lateral force increases from a minimum of 10 kN to a maximum of 1500 kN in 10 kN increments per step, while the load direction rotates clockwise around the flange axis by 10 degrees per time step. This approximates the complex loading conditions experienced by wind turbine flanges.

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3. Bolt Group Stress Distribution Characteristics

[FIGURE:2] shows the Mises stress distribution of the bolt group under pretension only. At this stage, the stress distribution around the flange circumference is essentially uniform. For individual bolts, the maximum stress occurs at the connection between the shank and bolt head, with a maximum equivalent stress of 475.3 MPa.

After the flange top surface is subjected to lateral forces, the bolt group stress distribution becomes non-uniform. [FIGURE:3] shows the Mises stress distribution at monitoring points on bolt shanks as lateral force increases from 900 kN to 950 kN. The stress distribution rotates correspondingly with changes in load direction. At 900 kN, all bolts remain in the elastic stage. As the load direction changes, the entire bolt group stress distribution rotates accordingly.

[FIGURE:4] shows the Mises stress distribution at monitoring points for lateral forces from 1450 kN to 1500 kN. At this stage, some bolts have exceeded the material yield strength. The overall stress level of the bolt group is significantly higher than in previous cases. After rotating the bolt stress distribution diagrams to align the lateral forces in the same orientation, the distribution remains approximately symmetric about the lateral force action line. The stress level in the half-circumference opposite the lateral force direction remains significantly higher than in the half-circumference in the force direction.

Under various lateral force levels, the bolt group stress distribution is never strictly symmetric about the lateral force action line, which is related to the changing history of the lateral force direction.

4. Neural Network Models

4.1 BP Neural Network The BP (Back Propagation) neural network is a multi-layer feedforward network trained using error backpropagation algorithm. Its computation process includes forward propagation of data signals and backward propagation of error signals. Gradient descent is used to adjust weights and thresholds between layers until the error meets the specified accuracy requirements [21]. The typical structure includes an input layer, one or more hidden layers, and an output layer.

In this study, the input to the input layer is the stress of 12 bolts, and the output from the output layer is the predicted stress of the remaining 24 bolts. During initialization, BP neural networks typically use random initial weights and thresholds, which may lead to suboptimal model performance [22]. Therefore, this study employs genetic algorithms and particle swarm algorithms to optimize the initial weights and thresholds of the BP neural network, creating GA-BP and PSO-BP neural network prediction models.

4.2 GA-BP Neural Network Genetic Algorithm (GA) is a parameter optimization method that utilizes replication, crossover, and mutation phenomena from natural selection and genetics for data optimization. It offers strong robustness and facilitates searching large solution spaces [23-26]. In the GA-BP neural network, GA optimizes the initial weights and thresholds of the BP network.

[FIGURE:5(b)] illustrates the GA optimization process for the neural network. The algorithm encodes the initial weights and thresholds of the BP neural network to create an initial population. The reciprocal of the root mean square error between network predictions and test set values serves as the fitness function for evaluating population chromosomes. Based on fitness values, the roulette wheel method selects high-fitness individuals for reproduction. Selected individuals exchange partial chromosome information to generate new offspring, and certain individuals undergo random mutation at low probability to increase genetic diversity. Through continuous evolution via selection, crossover, and mutation operations, the population’ s fitness values improve generation by generation until optimal initial weights and thresholds are obtained [27].

4.3 PSO-BP Neural Network Particle Swarm Optimization (PSO) is a population intelligence-based algorithm that simulates collective biological behavior, using a swarm of randomly distributed particles to find optimal solutions in multidimensional space [28]. Each particle represents a feasible solution in the search space, with initial velocity and position. Fitness function values evaluate the quality of particle positions. Particles continuously adjust their movement direction and velocity based on their own historical best position and the swarm' s historical best position to achieve optimization until the global optimal solution is found [29-31].

In optimizing the BP neural network with PSO, each particle represents the weights and thresholds between BP neural network layers. The algorithm updates particle velocity and position to obtain optimal initial weights and thresholds, forming the PSO-BP neural network model [FIGURE:5(c)].

4.4 Neural Network Model Setup For establishing the neural network models, the number of hidden layer neurons is typically determined using empirical formulas [32]:

$$h = \sqrt{m+n} + l$$

where l is an integer between 1 and 10, and m and n are the numbers of nodes in the input and output layers, respectively. Based on trial calculations and parameter sensitivity analysis, the number of hidden layer nodes is determined to be 12, with a single hidden layer.

When training the three neural network models, the maximum training epochs are set to 1000, and the minimum target error is 0.0001. For the GA-BP model, genetic algorithm parameters are: maximum genetic iterations = 100, population size = 50, crossover probability = 0.8, and mutation probability = 0.2. For the PSO-BP model, particle swarm algorithm parameters are: maximum iterations = 100, population size = 50, learning factor 1 = 1.5, and learning factor 2 = 1.5.

Based on the finite element simulation described above, 12 bolts are selected at intervals around the flange circumference, with their monitoring point stresses serving as neural network inputs. The monitoring point stresses of the remaining 24 bolts serve as neural network outputs.

Among the 150 finite element analysis steps, some bolts enter the plastic stage under large lateral force loads. To ensure data sample randomness and prediction model reliability, 60 analysis steps are randomly selected as the training set for neural network training, and 10 steps are selected as the test set for evaluating prediction performance.

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5. Prediction and Analysis of Flange Bolt Group Stress

[FIGURE:6(a)] plots the average relative error between predicted and finite element results for the 24 bolts in each prediction round using the three neural network models. The average relative errors for BP, GA-BP, and PSO-BP prediction models are 11.19%, 11.75%, and 12.26%, respectively, with minimum values of 0.99%, 0.86%, and 0.83%. When using relative error as the evaluation criterion, GA-BP and PSO-BP models show higher prediction accuracy than the basic BP model, with PSO-BP demonstrating the highest accuracy.

[FIGURE:7] compares the finite element simulation results with the prediction results from the three models for the 24 bolts in the round with smallest prediction error. In the finite element simulation, some bolts have stress levels exceeding the material yield strength (940 MPa), while others have relatively low stress levels (47.7 MPa). [FIGURE:7(b)] shows that all three prediction models exhibit larger relative errors when bolt stress is low (bolts 12-24) and smaller relative errors when bolt stress is high (bolts 1-11).

[FIGURE:8] compares the finite element results with predictions in the round with largest prediction error. [FIGURE:8(a)] shows the bolt group is entirely in the elastic stage, with maximum and minimum stresses of 526.4 MPa and 341.7 MPa, respectively. The smaller stress differences among bolts result in relatively small relative errors for all three prediction models [FIGURE:8(b)].

[FIGURE:9] examines the relationship between prediction accuracy and bolt group stress characteristics. [FIGURE:9(a)] shows a clear negative correlation between prediction relative error and the minimum bolt stress value—prediction accuracy decreases as the minimum bolt stress value in the flange bolt group decreases. [FIGURE:9(b)] shows a positive correlation between prediction relative error and the maximum stress difference in the bolt group—prediction accuracy decreases as the maximum stress difference increases. [FIGURE:9(c)] demonstrates that neural network model prediction accuracy is generally higher when the bolt group is in the elastic stage compared to when some bolts have entered the plastic stage.

For practical flange bolt stress monitoring, prediction accuracy at high stress levels is particularly important. Given the bolt material yield strength of 940 MPa, this study specifically analyzes prediction performance for bolts with monitoring point stress levels exceeding 400 MPa. [FIGURE:6(b)] shows the average relative error for bolts with stress values above 400 MPa in each prediction round. The maximum average relative errors for BP, GA-BP, and PSO-BP models are 5.31%, 5.13%, and 4.69%, respectively, with minimum values of 0.46%, 0.51%, and 0.56%.

Table 2 summarizes the prediction errors considering all bolts versus only those with stress above 400 MPa. When considering all bolts, the overall average errors for BP, GA-BP, and PSO-BP models are 4.64%, 4.11%, and 3.95%, respectively. When considering only bolts with stress values above 400 MPa, the corresponding average errors are 1.85%, 1.64%, and 1.62%. Among the three models, PSO-BP demonstrates the highest accuracy, while GA-BP shows higher accuracy than the basic BP model. For high-stress bolts above 400 MPa that warrant greater attention, all three models achieve high prediction accuracy.

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6. Conclusions

This study uses finite element simulation results of pretensioned flange connection bolts under varying flange end lateral force loads as data samples to predict and analyze bolt group stress using BP, GA-BP, and PSO-BP neural network models. The following conclusions are drawn:

1. Bolt group stress distribution characteristics vary with the magnitude and direction of lateral force loads. However, the maximum stress bolts are generally located opposite the lateral force action line, and the bolt group stress distribution exhibits approximate symmetry about the lateral force action line. The stress level in the half-circumference opposite the lateral force direction is significantly higher than in the half-circumference in the force direction.
2. Using relative error as the evaluation criterion, the prediction accuracy of all three neural network models decreases with decreasing minimum bolt stress value in the bolt group and increases with increasing maximum stress difference among bolts. Prediction accuracy is generally higher when the bolt group is in the elastic stage compared to when some bolts have entered the plastic stage.
3. GA-BP and PSO-BP models demonstrate higher accuracy than the basic BP model, with PSO-BP showing the highest accuracy. For high-stress bolts above 400 MPa that warrant greater attention, all three models provide high-precision predictions.

In future research, larger bolt quantities, more complex external load conditions, and the impact of input bolt number on prediction accuracy will be considered to make necessary improvements to the prediction model. Experimental testing and validation will also be conducted.

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