Study on the Axial Compressive Bearing Capacity of Tapered Concrete-Filled Double-Skin Steel Tubular Members Based on a Heuristic-Algorithm-Optimized BP Neural Network

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Abstract

To address the difficulty in calculating the axial compressive bearing capacity of tapered concrete-filled double skin steel tubular (TCFDST) members caused by sectional variation, heuristic algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), simulated annealing (SA), and ant colony optimization (ACO) were applied to a back propagation neural network (BPNN), and a TCFDST axial compressive bearing capacity prediction model combining global and local optimization was proposed. A total of 1362 sets of experimental and finite element simulation data were selected to establish a TCFDST axial compression database. Ten member dimensional and material parameters were used as input parameters, and the axial compressive bearing capacity was taken as the output parameter. Four BPNN models optimized by heuristic algorithms were established, respectively. By comparison with four classical machine learning algorithms and code formulas, it was demonstrated that the heuristic-algorithm-optimized BP neural network has higher prediction accuracy. Combined with parametric analysis, the variation patterns of the bearing capacity predicted by the model with each input parameter were obtained, verifying the general applicability of the prediction model. The BPNN axial compressive bearing capacity prediction model optimized based on heuristic algorithms can provide an important reference for solving the bearing capacity calculation problem of TCFDST structures and promoting their application.

Full Text

Study on the Axial Compressive Bearing Capacity of Tapered Concrete-Filled Double-Skin Steel Tubular Members Based on a Heuristic-Algorithm-Optimized BP Neural Network

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Abstract: To address the difficulty in calculating the axial compressive bearing capacity of tapered concrete-filled double-skin steel tubular (TCFDST) members caused by cross-sectional variation, this paper applies heuristic algorithms —including genetic algorithms (GA), particle swarm optimization (PSO), simulated annealing (SA), and ant colony optimization (ACO)—to a BP neural network (back propagation neural network, BPNN), and proposes a TCFDST axial compressive bearing-capacity prediction model that combines global and local optimization. A total of 1,362 sets of experimental and finite-element simulation data were selected to construct a TCFDST axial-compression database. Ten member-size and material parameters were adopted as input parameters, and the axial compressive bearing capacity was taken as the output parameter; four BPNN models optimized by heuristic algorithms were established respectively. By comparison with four classical machine-learning algorithms and code formulas, it is demonstrated that the BP neural network optimized by heuristic algorithms has higher prediction accuracy. Combined with parametric analysis, the variation laws between the bearing capacity predicted by the model and each input parameter were obtained, verifying the general applicability of the prediction model. The BPNN axial-compressive bearing-capacity prediction model optimized by heuristic algorithms can provide an important reference for solving bearing-capacity calculation problems and promoting the application of TCFDST structures.

Keywords: tapered concrete-filled double-skin steel tubular; axial compressive bearing capacity; heuristic algorithm; BP neural network; machine learning

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Compression bearing capacity of tapered concrete-filled double skin steel tubular members based on heuristic algorithm optimized BP neural network

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Abstract: To address the computational challenges posed by the cross-sectional variations in tapered concrete-filled double skin steel tubular (TCFDST), this paper employs four heuristic algorithms—genetic al-

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gorithms (GA), particle swarm optimization (PSO), simulated annealing (SA), and ant colony optimization (ACO) to enhance a backpropagation neural network (BPNN). This paper proposes a predictive model that integrates global and local optimization strategies. A database comprising 1 362 experimental and simulation results was established, with dimensional and material parameters as inputs and axial compressive capacity as the output. Four BPNN models optimized using heuristic algorithms were developed and validated against other machine learning algorithms and current design standards; the results indicate superior predictive accuracy. Parametric analysis reveals consistent relationships between the predicted load-bearing capacity and the various input variables. The proposed method provides a reliable reference for addressing the challenges of load-bearing capacity calculations for TCFDST structures.

Key words: tapered concrete-filled double skin steel tubular column; compression bearing capacity; heuristic algorithm; back propagation neural network; machine learning

Concrete-filled double skin steel tubular (CFDST) structures, owing to their excellent axial compression, flexural, torsional, fire-resistance, and impact-resistance performance, can serve as primary supporting structures for various long-span structures, bridge piers, underground structures, and high-rise or super high-rise buildings[1-2]. As the principal devices for generating wind energy, offshore and onshore wind turbines depend critically on the safety of their supporting structures to ensure the long-term safe operation of wind turbine units. Traditional wind-power support structures mostly adopt single-layer steel towers; when wind power exceeds 12 MW, the design height of the tower top section can reach 220 m. Under axial compression and eccentric compression loads from the upper nacelle and blades, such ultra-high single-layer steel tubular structures are prone to tower-collapse accidents because of insufficient axial bearing capacity[3-4].

The tapered concrete-filled double skin steel tubular (TCFDST) structure was developed from the traditional CFDST structure. Compared with ordinary CFDST columns, the cross section of TCFDST, which gradually increases from the bottom to the top, adapts to the cross-sectional bending moment that gradually increases along the column body under horizontal loads, thereby reducing the self-weight of the structure. However, its variable-section design also makes it impossible for designers to accurately apply existing CFDST design codes to select the calculated section and accurately compute the structural bearing capacity. Therefore, accurately predicting the axial compressive capacity of TCFDST members and reducing the redundancy rate in structural design are of significant value for promoting and applying TCFDST members as primary supporting structures in building design. In recent years, scholars in China and abroad have carried out extensive experimental studies on the axial compression performance of CFDST members and, on this basis, have established calculation formulas for axial compressive capacity through linear and nonlinear regression methods combined with confinement theory, unified theory, and superposition theory[5]. In addition to axial compressive capacity formulas based on mechanical principles, as machine-learning algorithms have gradually matured, applying deep-learning algorithms to engineering design to solve structural design problems has become a new approach in building structural design and performance analysis.

NGUYEN et al.[6] used the social chain search optimization (SCSO) algorithm, a gray wolf optimization–whale optimization algorithm, and artificial rabbit optimization (ARO) to tune the hyperparameters of the gradient boosting regression (GBR) algorithm, and analyzed the prediction accuracy of different optimization algorithms for the axial compressive capacity of CFDST. WANG et al.[7] adopted three methods—support vector machine (SVM), random forest regression (RFR), and neural network (NN)—to train eccentric-compression test samples of concrete-filled steel tube (CFST) members in a database, establishing a machine-learning model with dimensional and material parameters as the input layer and flexural bearing capacity as the output layer. HONG et al.[8], by comparing multiple machine-learning algorithms with code-based bearing-capacity calculation formulas, concluded that the K-nearest neighbors (KNN) algorithm has relatively high accuracy in predicting the axial compressive capacity of CFDST members. CHANDRAMOULI et al.[9] used six machine-learning models to predict the axial compressive capacity of CFDST members and proposed an optimal calculation model applicable to core concrete confined by various fiber composites and steel materials. Zhao Junhai et al.[10] compared and analyzed the prediction performance of a back propagation (BP) neural network (back propagation neural network, BPNN) and a particle swarm optimization–back propagation neural network (PSO-BPNN) for the axial compressive capacity of CFDST members, and recommended a member bearing-capacity prediction model in combination with domestic and international codes. Domestic and international codes mostly use the top minimum section and a modified length for conservative calculation of the bearing capacity of TCFDST members, leading to relatively large errors in the calculated bearing capacity[11–12]. Scholars in China and abroad have gradually broadened their focus to using machine-learning algorithms to predict the bearing capacity of CFDST, whereas for those with tapering

…and different hollow ratios remains insufficient for machine-learning prediction models of TCFDST members.

Following a data-driven strategy, the axial-compressive bearing capacities corresponding to axial-compression test data for 182 CFDST and TCFDST members and numerical simulation data for 1,180 TCFDST members were assembled into an analysis database. Heuristic algorithms, including the genetic algorithm, particle swarm optimization, simulated annealing, and ant colony optimization, were combined to optimize a multilayer feed-forward neural-network model for predicting the axial-compressive bearing capacity of TCFDST members, and the feasibility of the model was analyzed. The advantages of the heuristic-algorithm-optimized model were further assessed by comparison with several classical machine-learning algorithms—random forest regression, the K-nearest-neighbor algorithm, support vector machine regression, and radial basis function neural networks—as well as with code formulas for bearing capacity. Finally, parametric analysis was used to reveal the variation patterns between the model-predicted bearing capacity and the input variables.

1 Test Database

1.1 Finite Element Calculation Database

ABAQUS was used to establish a simulation model for axially compressed TCFDST members. The inner and outer steel tubes and the sandwiched concrete were modeled using S4R shell elements and C3D8R solid elements, respectively. The sandwiched concrete and steel adopted a shell–solid plastic damage constitutive model and a five-stage quadratic plastic-flow model, respectively [13 − 14]. Surface-to-surface contact was used between the inner and outer steel tubes and the sandwiched concrete; hard contact and the Coulomb friction model were adopted for the normal and tangential behaviors, respectively, with a friction coefficient of 0.6 [15 − 16]. At the loading end and the fixed end, MPC rigid beams were used to couple the inner and outer steel tubes and the sandwiched concrete to the centroidal reference point of the section. At the fixed end, translational degrees of freedom in the x, y, and z directions were constrained; at the loading end, loading was applied in the y direction while translational degrees of freedom in the x and z directions were constrained, as shown in Fig. 1. TCFDST members have strong plastic deformation capacity under axial compression, and residual stress has no significant effect on the peak bearing capacity of the members. Therefore, the effects of residual stress and initial imperfections on the axial-compression performance of the members were neglected in the analysis [17].

Fig. 1 labels: Disp; $U_x = U_z = 0$; RP_1; H; θ; D_{ib}; D_{ob}; RP_2, $U_x = U_y = U_z = 0$.

Fig. 1 Finite element model of a TCFDST member under axial compression

Fig. 1 TCFDST finite element model under axial compression

A total of six axial-compression test datasets for TCFDST members were selected for model validation. By comparing the consistency between the axial-compressive load-displacement curves and failure modes obtained from tests and numerical simulations in Refs. $[18-19]$, the effectiveness and accuracy of the numerical model in predicting the axial-compression behavior of TCFDST members were verified. The load-displacement curves and failure modes obtained from the literature tests and numerical simulations are shown in Figs. 2 and 3.

Fig. 2 subfigures and visible legends:
(a) $C1$[18]: C1-Test, C1-FEM-Ref, C1-FEM.
(b) $C2$[18]: C2-Test, C2-FEM-Ref, C2-FEM.
(c) $C3$[18]: C3-Test, C3-FEM-Ref, C3-FEM.
(d) $C4$[18]: C4-Test, C4-FEM-Ref, C4-FEM.
(e) $CT1$[19]: CT1-Test, CT1-FEM-Ref, CT1-FEM.
(f) $CT2$[19]: CT2-Test, CT2-FEM-Ref, CT2-FEM.
(g) $CT3$[19]: CT3-Test, CT3-FEM-Ref, CT3-FEM.
(h) $CT4$[19]: CT4-Test, CT4-FEM-Ref, CT4-FEM.
Axes: load/kN; displacement/mm.

Fig. 2 Load-displacement curves from numerical calculation and tests of TCFDST members under axial compression

Fig. 2 Load-displacement curves by numerical calculation and test of TCFDST members under compression

(a) C3-1 (b) CT2-2 (c) CT4-1

Fig. 3 Failure modes by numerical calculation and test of TCFDST members under compression [18-19]

1.2 Experimental Database

To use data-driven machine-learning algorithms to predict the axial compressive bearing capacity of TCFDST members, a database of axial compression of the members was first established. This database consists of axial-compression test data for 182 CFDST and TCFDST members, as well as validated finite-element simulation data for 1,180 TCFDST members. The parameters and axial compressive bearing capacities of the database samples are shown in Table 1.

Table 1 Basic information and sources of the TCFDST axial-compression database
Tab. 1 Source and summary of the TCFDST members database

Number	D_{ob}/mm	D_{ot}/mm	t_o/mm	D_{ib}/mm	D_{it}/mm	t_i/mm	H/mm	N_e/kN	Reference
6	114.00~3[illegible]	114.00~30[illegible]	3.00	48.00~16[illegible]	48.00~165[illegible]	3.00	342.00~9[illegible]	[illegible]~3 331.00	[20]
1	165.00	165.00	3.54	60.00	60.00	2.85	480.00	1 660.00	[21]

Number	D_{ob}/mm	D_{ot}/mm	t_o/mm	D_{ib}/mm	D_{it}/mm	t_i/mm	H/mm	N_e/kN	Reference
9	538.00	538.00	3.76~5.6[illegible]	418.00~4[illegible]	[illegible]	[illegible]	1 500.00	5 966.80~8 949.70	[22]
5	250.00~3[illegible]	[illegible]	[illegible]	165.00~2[illegible]	[illegible]	[illegible]	750.00~1 050.00	3 103.00~5 448.00	[18]
12	164.80~1[illegible]	[illegible]	[illegible]~6.0[illegible]	[illegible]2.50~76[illegible]	[illegible]	[illegible]~3.2[illegible]	[illegible]95.00	1 831.00~3 322.00	[23]
9	157.00~1[illegible]	[illegible]	[illegible]~2.1[illegible]	[illegible]8.00~1[illegible]	[illegible]	[illegible]~2.1[illegible]	[illegible]50.00	378.00~96[illegible]	[24]
2	356.00	356.00	5.50	168.00~2[illegible]	[illegible]	[illegible]	1 068.00	7 242.00~8 516.00	[25]
8	114.30	114.30	2.73~5.8[illegible]	[illegible]0.30	60.30	2.52~5.7[illegible]	[illegible]45.00	734.60~1 666.41	[26]
12	188.90~1[illegible]	[illegible]	[illegible]~6.7[illegible]	[illegible]3.70~10[illegible]	[illegible]	[illegible]~4.1[illegible]	[illegible]70.00	2 376.00~3 286.00	[27]
6	398.00	300.00~3[illegible]	[illegible]~3.5[illegible]	[illegible]92.00~3[illegible]	[illegible]	[illegible]~3.00	1 465.00	2 094.00~2 885.00	[28]
12	170.00~1[illegible]	[illegible]	[illegible]	115.00~1[illegible]	[illegible]	[illegible]	510.00~570.0[illegible]	[illegible] 100.00~1 420.00	[19]
5	300.00~3[illegible]	[illegible]	[illegible]~5.9[illegible]	[illegible]10.00~3[illegible]	[illegible]	[illegible]~5.9[illegible]	[illegible]00.00~1 080.00	6 051.00~9 950.00	[29]
16	139.20~1[illegible]	[illegible]	[illegible]~3.5[illegible]	[illegible]6.00	76.00	2.00	1 000.00~2 500.00	732.10~1 263.50	[30]
8	140.00~1[illegible]	[illegible]	[illegible]~5.0[illegible]	[illegible]8.00~78[illegible]	[illegible]	[illegible]~5.0[illegible]	[illegible]00.00	1 223.70~1 852.20	[31]
9	114.30~1[illegible]	[illegible]	[illegible]~6.0[illegible]	[illegible]8.30~10[illegible]	[illegible]	[illegible]~3.3[illegible]	[illegible]00.00~500.0[illegible]	[illegible] 145.00~1 665.00	[32]
9	538.00	538.00	3.76~5.6[illegible]	418.00~4[illegible]	[illegible]	[illegible]	1 507.00	5 966.80~8 949.70	[33]
9	160.00	160.00	1.00~2.1[illegible]	[illegible]7.00~11[illegible]	[illegible]	[illegible]~2.1[illegible]	[illegible]00.00	378.00~96[illegible]	[34]
4	398.20~4[illegible]	[illegible]	[illegible]~3.0[illegible]	[illegible]39.60~2[illegible]	[illegible]	[illegible]~3.02	1 002.00~3 502.00	2 [illegible]23.00~3 423.00	[35]

Number	D_{ob}/mm	D_{ot}/mm	t_o/mm	D_{ib}/mm	D_{it}/mm	t_i/mm	H/mm	N_e/kN	Reference
2	114.30	114.30	2.73~5.85	60.30	60.30	2.56~4.73	343.00	758.61~1 622.25	[36]
3	160.00	160.00	2.99	60.00	60.00	2.00	420.00	1 487.00~1 542.00	[37]
6	140.00~450.00	140.00~450.00	2.50~8.00	76.00~406.00	76.00~406.00	1.60~8.00	420.00~700.00	701.30~8 906.00	[38]
5	203.00~300.00	203.00~300.00	4.00~6.00	76.00~203.00	76.00~203.00	4.00	600.00~900.00	4 751.40~9 783.80	[39]
8	270.00~320.00	240.00~290.00	6.00	170.00~320.00	120.00~170.00	4.00	1 500.00~3 000.00	8 027.13~11 016.61	[40]
6	250.00~350.00	250.00~300.00	6.00	100.00~135.00	135.00~135.00	5.00	150.00	8 628.00~12 015.00	[41]

Table 1 (continued)

Quantity	D_{ob}/mm	D_{ot}/mm	t_o/mm	D_{ib}/mm	D_{it}/mm	t_i/mm	H/mm	N_e/kN	Reference
8	165.00–273.00	165.00–273.00	2.45–2.78	89.00–165.00	89.00–165.00	2.68–3.00	495.00–819.00	1 320.00–4 845.00	[42]
2	120.00	120.00	1.96	60.00	60.00	1.96	1 324.00	578.00–715.00	[43]
1 180	360.00–740.00	360.00	2.50–6.00	110.00–715.00	110.00–335.00	2.50–6.00	1 000.00–3 000.00	3 181.73–7 661.93	FEM

Note: D_{ob}, D_{ot}, and t_o are the diameters at the top and bottom and the wall thickness of the outer steel tube; D_{ib}, D_{it}, and t_i are the diameters at the top and bottom and the wall thickness of the inner steel tube; H is the member height; and N_e is the measured axial compressive bearing capacity of the member.

The cited studies tested concrete specimens of sizes specified by different codes to obtain the concrete compressive strength, where $f_{\mathrm{cy,100}}$ is the compressive strength of a cylindrical specimen with a diameter of 100 mm, $f_{\mathrm{cu,150}}$ is the compressive strength of a cubic specimen with a side length of 150 mm, and $f_{\mathrm{cu,100}}$ is the compressive strength of a cubic specimen with a side length of 100 mm.

Because the various concrete strengths do not have common statistical characteristics, they were converted, with reference to Eq. (1) given in Ref. [7], into $f_{\mathrm{cy},150}$, the standard cylindrical compressive strength:

$$f_{\mathrm{cy},150} = \begin{cases} 1.67 \times 150^{-0.112} f_{\mathrm{cy},100} \\ \left[0.76 + 0.2 \lg\left(\dfrac{f_{\mathrm{cu},150}}{19.6}\right)\right] f_{\mathrm{cu},150} \\ 0.9 f_{\mathrm{cu},100} \end{cases} \tag{1}$$

The database samples were tested using the Shapiro–Wilk method. The results showed significance ($P < 0.05$); the absolute kurtosis of the samples was less than 10 and the absolute skewness was less than 3. The normal plots were essentially bell-shaped, and the samples can basically be accepted as normally distributed, as shown in Fig. 4.

Visible subplot annotations in Fig. 4:

- (a) D_{ob}: diameter/mm; frequency; mean = 444.06; standard deviation = 126.71.
- (b) D_{ot}: diameter/mm; frequency; mean = 342.38; standard deviation = 63.01.
- (c) t_o: thickness/mm; frequency; mean = 3.11; standard deviation = 0.62.
- (d) D_{ib}: diameter/mm; frequency; mean = 319.59; standard deviation = 131.41.
- (e) D_{it}: diameter/mm; frequency; mean = 217.79; standard deviation = 81.17.
- (f) t_i: thickness/mm; frequency; mean = 3.03; standard deviation = 0.51.
- (g) f_c: compressive strength/MPa; frequency; mean = 43.92; standard deviation = 12.94.
- (h) f_{syo}: yield strength/MPa; frequency; mean = 423.78; standard deviation = 74.58.
- (i) f_{syi}: yield strength/MPa; frequency; mean = 420.80; standard deviation = 70.13.

Fig. 4 Parametric distribution of some basic input parameters in the database of TCFDST members under axial compression.

To intuitively analyze whether there is a strong correlation between the input parameters and the output parameters, Pearson, Spearman, and Kendall methods were used to calculate the correlation coefficients between the input and output parameters, as shown in Fig. 5.

Fig. 5 Correlation coefficients between input parameters and output parameters

Fig. 5 Correlation coefficient between input parameter and output parameter

2 Load-Bearing Capacity Prediction Based on BP Neural Networks

2.1 Standard BP Neural Network

The standard BPNN model includes two processes: forward propagation and backpropagation. In forward propagation, input data pass through the hidden layer to the output layer, and the output of each node is obtained by weighted summation and computation with the activation function. In backpropagation, the error between the output and the expected value is propagated backward, and the error is reduced by adjusting the weights and thresholds

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The core idea of the BPNN algorithm is to continuously adjust the weights and thresholds of the network according to the network output error, so that the final output of the network is as close as possible to the expected output. Since the weights and thresholds of a BPNN are usually randomly initialized before training begins, the initial values have an important influence on the training performance of the network; therefore, how to select the optimal initial weights and thresholds is critical.

2.2 BP Neural Network Optimized by Genetic Algorithm

The genetic algorithm (GA) is a search and optimization algorithm that simulates natural selection and genetic mechanisms. Through operations such as selection, crossover (hybridization), and mutation, it simulates the "survival of the fittest" principle in Darwinian evolutionary theory within a population of solutions, with the aim of finding the optimal solution.

The genetic algorithm searches the global variable space through population selection, crossover, and mutation, thereby avoiding the problem that random values may cause gradient descent to fall into a local optimum. The main procedure is as follows: encoding: convert the weights and thresholds of the BPNN model into chromosomes, i.e., the encoding process; initialization: randomly generate a certain number of individuals as the initial population; fitness evaluation: take the error of the trained network when applied to the validation set as the fitness-evaluation criterion—the smaller the error, the higher the individual fitness; selection: use roulette-wheel selection to select individuals with high fitness; crossover and mutation: generate new individuals through crossover and mutation of the encoding to increase population diversity; generation of a new population: form a new population from the individuals after selection, crossover, and mutation, replacing the original population; termination condition: terminate the optimization when the maximum number of iterations is reached or when the fitness satisfies the preset threshold.

2.3 BP Neural Network Optimized by Particle Swarm Algorithm

Particle swarm optimization (PSO) is an optimization algorithm based on swarm intelligence that simulates the foraging behavior of bird flocks. In the PSO algorithm, each solution is regarded as a particle in the solution space, and each particle has its own position and velocity. The optimal solution is sought by simulating the flight of each particle (solution) in the solution space.

The particle swarm algorithm dynamically adjusts and searches the global variable space by continuously updating the velocity and position information of particles, in order to find the weight and threshold configuration that enables the BPNN model to achieve the minimum error. The main procedure is as follows: initialization: randomly initialize the position and velocity of each particle in the swarm; fitness evaluation: train the network using the training set and evaluate the network performance using the validation set, taking the error as the fitness-evaluation criterion; update the individual and global optima: for each particle, update its individual optimum and the global optimum of the entire swarm; update velocity and position: update the velocity and position of each particle according to the current velocity, the individual optimum, and the global optimum; termination condition: terminate the optimization when the maximum number of iterations is reached or when the fitness satisfies the preset threshold.

2.4 BP Neural Network Optimized by Simulated Annealing Algorithm

The simulated annealing algorithm (SA) is a probabilistic search algorithm based on the annealing process of materials. During annealing, a material is heated and then slowly cooled; its internal structure becomes disordered during heating, and as it cools slowly, atoms gradually move to lower-energy states, ultimately reaching a more stable structure.

The simulated annealing algorithm determines the probability of accepting a new solution through the cooling process of the system from high temperature to low temperature, and effectively searches the global variable space by setting random perturbations, thereby seeking the global optimum. The main procedure is as follows: initialization: set a high initial temperature, cooling rate, etc.; fitness evaluation: train the network using the training set and evaluate the network performance using the validation set, taking the error as the fitness-evaluation criterion; generate and evaluate a new solution: based on the current solution, generate a new weight and threshold configuration (i.e., a new solution) through random perturbation; acceptance criterion: if the solution is better, use it; otherwise, determine the acceptance probability of the solution using the temperature and the difference between solutions; lower the system temperature according to the prescribed cooling rate, and then

Then the above steps of generating a new solution and applying the acceptance criterion are repeated until the stopping condition is satisfied.

2.5 Optimization of the BP Neural Network by the Ant Colony Algorithm

Ant colony optimization (ACO) is a heuristic algorithm that simulates the foraging behavior of ants in nature. It is mainly used to solve path-optimization problems, such as the traveling salesman problem (TSP) and the vehicle routing problem (VRP).

The ant colony algorithm marks paths by releasing pheromones as ants move, and other ants choose paths according to the retained pheromone concentration on those paths. The main procedure is as follows: initialization: set parameters such as the colony size, pheromone evaporation rate, and pheromone importance factor, and calculate the pheromone concentration on all paths; fitness evaluation: construct the objective function and minimize the network training error; pheromone updating: each ant selects a path according to the pheromone concentration and heuristic information, such as the magnitude of the weights and their relevance to the problem, that is, it selects the combination of weights and thresholds in the BPNN; selection of new weights and thresholds: at the end of each generation, the pheromone is updated according to the best solution found by all ants or the best solution in the current iteration, so as to increase the probability of successfully finding a better solution in subsequent iterations; model evaluation: the performance of the BPNN is evaluated on the validation set according to the new weights and thresholds; termination condition: when the maximum number of iterations is reached or the BPNN performance satisfies the preset threshold, the algorithm terminates.

The structural procedure for optimizing the BP neural network using the above four heuristic algorithms is shown in Fig. 6. First, the heuristic algorithm is used to select the initial weights and thresholds of the BPNN model; then the L-M (LEVENBERG-MARQUARDT) method is adopted to train the database samples and obtain the calculated weights and thresholds of the prediction model. During this process, the heuristic algorithm continuously optimizes the values of the weights and thresholds within the initial value range until the initial value that yields the minimum calculated RMSE within the number of iterations is found, which constitutes global optimization. Subsequently, the heuristic algorithm is used to perform secondary adjustment of the calculated weights and thresholds; the L-M method is no longer used for network training, and instead the prediction error is substituted into the heuristic algorithm to adjust the calculated weights and thresholds, which constitutes local optimization. To avoid model overfitting, the heuristic algorithm takes the simultaneous reduction of errors in both the training set and the validation set as the optimization criterion. In summary, selecting global and local optimization strategies can enable the BPNN model to achieve higher accuracy and broader applicability.

Translated text in Fig. 6:

- **TCFDST axial-compression database**
  - Literature test data
  - Finite-element calculation data
- **Data correlation analysis**
  - a) Input parameter types
    - 7 member dimensional parameters
    - 2 steel material parameters
    - 1 concrete material parameter
  - b) Output parameter
    - Axial compressive bearing capacity
- **Dataset preprocessing**
  Random sequence partitioning
- **Dataset partitioning**
- **Optimal training model**
- **Heuristic-algorithm-optimized BPNN model**
- **Optimized learning rate (L_0) and number of hidden-layer nodes** n_h
- **BPNN hyperparameter optimization**
  - BPNN model prediction
  - Validation set (15%)
  - BPNN model training
  - Training set (70%)
- **Optimal BPNN model testing**
- **Heuristic algorithms: GA/PSO/SA/ACO**
  - Standard BPNN model training
  - Weights I_w, threshold b
  - Define the fitness function (Globalfitness)
  - $i = i + 1$
  - GA/PSO/SA/ACO global optimization objective $\min(E_{\text{train}})$ and judgment:
    $E_{\text{train}}(i) < \min(E_{\text{train}})$ && $E_{\text{valid}}(i) < \min(E_{\text{valid}})$
  - Weights I_w, threshold b
  - Define the fitness function (Localfitness)
  - $i = i + 1$
  - GA/PSO/SA/ACO local optimization objective $\min(E_{\text{train}})$ and judgment:
    $E_{\text{train}}(i) < \min(E_{\text{train}})$ && $E_{\text{valid}}(i) < \min(E_{\text{valid}})$
- **Globalfitness**
  - LEVENBERG-MARQUARDT

  - BPNN model training: training set (train)
  - BPNN model validation: validation set (valid)
  - $E_{\text{train}}(i)$, $E_{\text{valid}}(i)$
- **Localfitness**
  - BPNN model prediction: training set (train)
  - BPNN model prediction: validation set (valid)
  - $E_{\text{train}}(i)$, $E_{\text{valid}}(i)$
- **Test set (15%)**

Fig. 6 Architecture diagram of the BPNN model optimized by heuristic algorithms

Fig. 6 Architecture description of the BPNN based on optimization algorithm

2.6 Model Evaluation Indicators

When machine-learning algorithms are used to predict axial compressive bearing capacity, the following indicators are commonly adopted to measure the accuracy and reliability of the prediction results. Root mean square error ($\varepsilon_{\text{RMSE}}$): the square root of the mean squared difference between the predicted value and the actual value, used to measure the discrepancy between the predicted and actual values; mean absolute error (ε_{MAE}): the mean of the absolute differences between the actual and predicted values, used to evaluate the deviation of the prediction results; mean absolute percentage error ($\varepsilon_{\text{MAPE}}$): the mean of the absolute difference between the actual and predicted values divided by the actual value, usually expressed as a percentage; coefficient of determination (R^2): reflects the degree of fitting between the actual and predicted values, with R^2 lying in the interval $[0, 1]$.

$$\varepsilon_{\text{RMSE}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{2}$$

$$\varepsilon_{\text{MAE}} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{3}$$

$$\varepsilon_{\text{MAPE}} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \tag{4}$$

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \Big/ \sum_{i=1}^{n}(y_i - \bar{y})^2 \tag{5}$$

where $\hat{y}_i$ is the model-predicted value, y_i is the true value, $\bar{y}$ is the mean of the true values, and n is the number of test samples.

2.7 Hyperparameter Tuning

The experimentally measured data and numerical simulation data were integrated into a unified database and randomly shuffled and divided. To avoid overfitting of the model to specific data, the hold-out method was used to divide the data into training, validation, and test sets at a ratio of $70 : 15 : 15$. Through 10 random divisions and averaging of the performance calculations, the uncertainty caused by a single division was reduced [6]. For the hyperparameter calculation of the BPNN model, the range of hidden-layer node numbers was calculated by Eq. (5), and the search range of the learning rate was set to $[0.005, 0.145]$. By setting the error matrices corresponding to the number of hidden-layer nodes and the learning rate, the training set and validation set were trained 50 times, and heat maps of the mean validation-set errors corresponding to the hyperparameters were obtained, as shown in Fig. 7.

The parameters corresponding to the minimum mean $\varepsilon_{\mathrm{RMSE}}$ obtained by the prediction model were selected as the baseline hyperparameters of the BPNN network; the recommended network hyperparameters of the BP neural network are shown in Table 2. Among them, the activation function of the hidden layer adopts the `tansig` function, and the activation function of the output layer adopts the `purelin` function. When different optimization algorithms are used to perform initial tuning of the BPNN weights and thresholds, different population sizes have a certain influence on the final model error accuracy. Usually, a larger population size improves the global search capability of the optimization algorithm, but also increases the computation time.

$$n_h = \sqrt{n_i + n_o} + \alpha \tag{6}$$

where n_h is the number of hidden-layer nodes, n_i is the number of input-layer nodes, n_o is the number of output-layer nodes, and α is any integer in $[1, 10]$.

Table 2. Recommended network hyperparameters for BPNN

Hyperparameter name	Value
Number of input-layer nodes (n_i)	10
Number of output-layer nodes (n_o)	1
Number of hidden-layer nodes (n_h)	15
Learning rate (L_0)	0.105

Therefore, four initial population sizes were selected for model calculation, as shown in Fig. 8. When the initial population size was $n_p = 30$, all four optimization models obtained relatively good global optimal solutions, with a moderate time cost.

Fig. 7. Error optimization heatmap under the influence of the number of hidden-layer nodes and learning rate

Subfigures: (a) RMSE; (b) MAE; (c) MAPE.
Axes: hidden-layer node count; learning rate. Color bars: $\varepsilon_{\mathrm{RMSE}}$, $\varepsilon_{\mathrm{MAE}}$, and $\varepsilon_{\mathrm{MAPE}}$/%.

Fig. 8. $\varepsilon_{\mathrm{RMSE}}$-iteration curves for the training set and validation set under different initial populations

Subfigures: (a) $n_p = 10$; (b) $n_p = 20$; (c) $n_p = 30$.
Axes: $\varepsilon_{\mathrm{RMSE}}$; number of iterations.
Legends: GA—training set; GA—validation set; PSO—training set; PSO—validation set; ACO—training set; ACO—validation set; SA—training set; SA—validation set. Reference lines: BPNN—validation set = 178.54; BPNN—training set = 124.56.

3 Comparison of Optimization Effects

3.1 Comparison of Model Performance Metrics

Based on the above hyperparameter optimization results and the recommended initial population sizes, the error metrics of the standard BPNN model and the BPNN models optimized by four heuristic algorithms on the training set and validation set were calculated, respectively. The calculation results are shown in Table 3.

As shown in Fig. 9(a), compared with the BPNN model, the GA-BPNN model reduced the training-set $\varepsilon_{\mathrm{RMSE}}$ by 58.03%, $\varepsilon_{\mathrm{MAE}}$ by 56.07%, and $\varepsilon_{\mathrm{MAPE}}$ by 59.02%, while increasing the goodness of fit R^2 to 0.9992; for the validation set, $\varepsilon_{\mathrm{RMSE}}$ decreased by 36.74%, $\varepsilon_{\mathrm{MAE}}$ by 42.27%, and $\varepsilon_{\mathrm{MAPE}}$ by 43.99%, while the goodness of fit R^2 increased to 0.9959. The optimization performance of the GA-BPNN model depends to a large extent on the degree of exploration of the global solution space, which helps avoid local minima and thereby better optimize the weights and thresholds.

Table 3 Characteristic parameters of multiple machine-learning models for predicting axial compression bearing capacity

Tab. 3 Characteristic parameters for multiple machine learning models for predicting axial compression bearing capacity

Algorithm model	Training set $\varepsilon_{\mathrm{RMSE}}$	Training set $\varepsilon_{\mathrm{MAE}}$	Training set R^2	Training set $\varepsilon_{\mathrm{MAPE}}$/%	Validation set $\varepsilon_{\mathrm{RMSE}}$	Validation set $\varepsilon_{\mathrm{MAE}}$	Validation set R^2	Validation set $\varepsilon_{\mathrm{MAPE}}$/%	Test set $\varepsilon_{\mathrm{RMSE}}$	Test set $\varepsilon_{\mathrm{MAE}}$	Test set R^2	Test set $\varepsilon_{\mathrm{MAPE}}$/%
BPNN	124.561	60.807	0.975	1.98	178.542	74.612	0.972	2.12	187.373	71.875	0.973	1.90
RF	516.788	242.522	0.917	7.02	567.114	254.308	0.897	7.93	545.259	260.577	0.885	8.32
KNN	86.334	68.617	0.970	2.46	302.461	131.776	0.941	3.48	193.033	110.056	0.946	2.84
SVR	442.467	226.566	0.939	5.49	459.846	235.788	0.930	6.44	436.429	244.619	0.926	7.16
RBFNN	87.783	52.075	0.998	1.65	181.742	70.049	0.989	1.86	265.422	121.346	0.973	2.78

Algorithm model	Training set $\varepsilon_{\mathrm{RMSE}}$	Training set $\varepsilon_{\mathrm{MAE}}$	Training set R^2	Training set $\varepsilon_{\mathrm{MAPE}}$/%	Validation set $\varepsilon_{\mathrm{RMSE}}$	Validation set $\varepsilon_{\mathrm{MAE}}$	Validation set R^2	Validation set $\varepsilon_{\mathrm{MAPE}}$/%	Test set $\varepsilon_{\mathrm{RMSE}}$	Test set $\varepsilon_{\mathrm{MAE}}$	Test set R^2	Test set $\varepsilon_{\mathrm{MAPE}}$/%
GA-BPNN	51.152	26.710	0.999	0.81	112.937	43.095	0.996	1.19	127.912	44.544	0.991	1.09
PSO-BPNN	53.552	26.681	0.999	0.82	81.649	38.923	0.998	1.18	147.580	47.832	0.994	1.12
SA-BPNN	73.962	34.860	0.998	1.18	87.891	42.128	0.998	1.57	100.595	43.768	0.996	1.13
ACO-BPNN	56.933	26.813	0.999	0.81	83.856	39.947	0.998	1.26	117.150	48.287	0.996	1.11

As shown in Fig. 9(b), compared with the BPNN model, the PSO-BPNN model reduced the training-set $\varepsilon_{\mathrm{RMSE}}$ by 57.01%, $\varepsilon_{\mathrm{MAE}}$ by 56.12%, and $\varepsilon_{\mathrm{MAPE}}$ by 58.67%, while increasing the goodness of fit R^2 to 0.9991; for the validation set, $\varepsilon_{\mathrm{RMSE}}$ decreased by 54.27%, $\varepsilon_{\mathrm{MAE}}$ by 47.83%, and $\varepsilon_{\mathrm{MAPE}}$ by 44.22%, while the goodness of fit R^2 increased to 0.9979. The optimization performance of the PSO-BPNN model depends on parameters such as particle swarm positions and inertia weights. By preventing the model from prematurely converging to a suboptimal solution, the overall performance of the model on the training set and validation set is improved.

As shown in Fig. 9(c), compared with the BPNN model, the SA-BPNN model reduced the training-set $\varepsilon_{\mathrm{RMSE}}$ by 40.62%, $\varepsilon_{\mathrm{MAE}}$ by 42.67%, and $\varepsilon_{\mathrm{MAPE}}$ by 40.47%, while increasing the goodness of fit R^2 to 0.9983; for the validation set, $\varepsilon_{\mathrm{RMSE}}$ decreased by 50.77%, $\varepsilon_{\mathrm{MAE}}$ by 43.54%, and $\varepsilon_{\mathrm{MAPE}}$ by 25.89%, while the goodness of fit R^2 increased to 0.9975. The optimization performance of the SA-BPNN model stems from its ability to accept poorer solutions to avoid the algorithm falling into local minima, which is beneficial for selecting solutions after the initial iterations. However, when the search space for solutions is large, compared with algorithms such as GA and PSO, the SA-BPNN model converges relatively slowly, which limits the optimization efficiency of the model. At the same time, the choice of cooling schedule and initial temperature has an important influence on model convergence; therefore, its optimization effect is relatively poor.

As shown in Fig. 9(d), compared with the BPNN model, the ACO-BPNN model reduced the training-set $\varepsilon_{\mathrm{RMSE}}$ by 54.29%, $\varepsilon_{\mathrm{MAE}}$ by 55.91%, and $\varepsilon_{\mathrm{MAPE}}$ by 59.38%, while increasing the goodness of fit R^2 to 0.9990; for the validation set, $\varepsilon_{\mathrm{RMSE}}$ decreased by 53.03%, $\varepsilon_{\mathrm{MAE}}$ by 46.46%, and $\varepsilon_{\mathrm{MAPE}}$ by 40.74%, while the goodness of fit R^2 increased to 0.9977. The ACO-BPNN model searches for and reinforces the selection probability of the optimal path through an iterative process. However, owing to the pheromone-updating mechanism, ACO converges more slowly than optimization algorithms such as GA and PSO, and parameters such as pheromone evaporation rate and transition probability affect the convergence speed of the model.

From the error analysis of the training set and validation set, it can be seen that heuristic optimization algorithms can improve the learning performance of the BPNN model on the training set and reduce the prediction error on the validation set. Because the validation-set error is introduced into heuristic algorithms as the fitness function for optimization, new data must be used to test the optimized network. Therefore, 200 new sample data points were selected to test the final optimized models, as shown in Table 3.

Fig. 9. Distribution of predicted bearing capacity and measured bearing capacity obtained by GA-, PSO-, SA-, and ACO-optimized BPNN models

- Common axes:
  - Vertical axis: axial compressive bearing capacity (predicted value) / (10^3 kN)
  - Horizontal axis: axial compressive bearing capacity (measured value) / (10^3 kN)
  - Reference lines: $y = x$, $y = x \pm 10\%$, $y = x \pm 20\%$
- **(a) GA-BPNN optimization results (training set and validation set)**
  Legend: GA-BPNN—training set; GA-BPNN—validation set.
  Training set: $R^2 = 0.9992$, $\varepsilon_{\mathrm{RMSE}} = 51.15$, $\varepsilon_{\mathrm{MAE}} = 26.71$, $\varepsilon_{\mathrm{MAPE}} = 0.81\%$.
  Validation set: $R^2 = 0.9959$, $\varepsilon_{\mathrm{RMSE}} = 112.94$, $\varepsilon_{\mathrm{MAE}} = 43.09$, $\varepsilon_{\mathrm{MAPE}} = 1.19\%$.
- **(b) PSO-BPNN optimization results (training set and validation set)**
  Legend: PSO-BPNN—training set; PSO-BPNN—validation set.
  Training set: $R^2 = 0.9991$, $\varepsilon_{\mathrm{RMSE}} = 53.55$, $\varepsilon_{\mathrm{MAE}} = 26.68$, $\varepsilon_{\mathrm{MAPE}} = 0.82\%$.
  Validation set: $R^2 = 0.9979$, $\varepsilon_{\mathrm{RMSE}} = 81.65$, $\varepsilon_{\mathrm{MAE}} = 38.92$, $\varepsilon_{\mathrm{MAPE}} = 1.18\%$.
- **(c) SA-BPNN optimization results (training set and validation set)**
  Legend: SA-BPNN—training set; SA-BPNN—validation set.
  Training set: $R^2 = 0.9983$, $\varepsilon_{\mathrm{RMSE}} = 73.96$, $\varepsilon_{\mathrm{MAE}} = 34.86$, $\varepsilon_{\mathrm{MAPE}} = 1.18\%$.
  Validation set: $R^2 = 0.9975$, $\varepsilon_{\mathrm{RMSE}} = 87.89$, $\varepsilon_{\mathrm{MAE}} = 42.13$, $\varepsilon_{\mathrm{MAPE}} = 1.57\%$.
- **(d) ACO-BPNN optimization results (training set and validation set)**

Legend: ACO-BPNN—training set; ACO-BPNN—validation set.
Training set: $R^2 = 0.9990$, $\varepsilon_{\mathrm{RMSE}} = 56.93$, $\varepsilon_{\mathrm{MAE}} = 26.81$, $\varepsilon_{\mathrm{MAPE}} = 0.81\%$.
Validation set: $R^2 = 0.9977$, $\varepsilon_{\mathrm{RMSE}} = 83.86$, $\varepsilon_{\mathrm{MAE}} = 39.95$, $\varepsilon_{\mathrm{MAPE}} = 1.26\%$.

Among them, for the GA-BPNN model, the test-set error indices $\varepsilon_{\mathrm{RMSE}}$, $\varepsilon_{\mathrm{MAE}}$, and $\varepsilon_{\mathrm{MAPE}}$ decreased by 31.73%, 38.03%, and 42.63%, respectively, and the goodness of fit R^2 increased to 0.991. For the PSO-BPNN model, the test-set error indices $\varepsilon_{\mathrm{RMSE}}$, $\varepsilon_{\mathrm{MAE}}$, and $\varepsilon_{\mathrm{MAPE}}$ decreased by 21.24%, 33.45%, and 41.05%, respectively, and the goodness of fit R^2 increased to 0.994. For the SA-BPNN model, the test-set error indices $\varepsilon_{\mathrm{RMSE}}$, $\varepsilon_{\mathrm{MAE}}$, and $\varepsilon_{\mathrm{MAPE}}$ decreased by 46.31%, 39.11%, and 40.53%, respectively, and the goodness of fit R^2 increased to 0.996. For the ACO-BPNN model, the test-set error indices $\varepsilon_{\mathrm{RMSE}}$, $\varepsilon_{\mathrm{MAE}}$, and $\varepsilon_{\mathrm{MAPE}}$ decreased by 37.48%, 32.82%, and 41.58%, respectively, and the goodness of fit R^2 increased to 0.996.

In summary, the BPNN models optimized using algorithms such as GA, PSO, SA, and ACO not only exhibit high fitting accuracy for the original sample data in the training set, but also maintain good validation performance on the validation set, and achieve relatively high prediction accuracy on the final test set. The global and local optimization strategies of the heuristic algorithms are evaluated through the validation-set error, effectively improving the learning efficiency of the BPNN model for the training samples. This strategy clarifies the direction for reducing the errors of the training set and validation set, ensures the prediction accuracy of the final model, and reduces the risk of network overfitting and underfitting.

3.2 Comparison with Other Machine Learning Methods

To comparatively analyze the advantages of the BPNN models optimized by the four heuristic algorithms over other classical machine learning algorithms, four classical machine learning algorithms were selected: random forest (RF), K-nearest neighbors (KNN), support vector regression (SVR), and radial basis function neural network (RBFNN). The same training set, validation set, and test set described above were used to evaluate the learning and prediction performance of the various algorithms. The results of the feature calculation parameters are shown in Table 3.

As shown in Fig. 10, among the four classical machine learning algorithms, the random forest (RF) algorithm yields the largest prediction errors for the training set, validation set, and test set, followed by the support vector regression (SVR) algorithm. Compared with the above two algorithms, the K-nearest neighbors (KNN) algorithm shows reduced prediction errors, while the prediction errors of the radial basis function neural network (RBFNN) algorithm are close to those of the standard BPNN algorithm. In summary, compared with common machine learning algorithms, the error indices ($\varepsilon_{\mathrm{RMSE}}, R^2, \varepsilon_{\mathrm{MAPE}}, \varepsilon_{\mathrm{MAE}}$) obtained by the proposed prediction model are superior for the training set, validation set, and test set.

Fig. 10 Column charts of the error metrics of different machine-learning models (a) RMSE; (b) MAE; (c) R^2; (d) MAPE
Legend: training set; validation set; test set.
Horizontal axis: prediction model.

4 Comparison of Code-Calculation Results

Existing bearing-capacity calculation methods usually use the calculation formulas for straight CFDST members and adopt the dimensional parameters of the top cross section of the conical member to approximately calculate the axial-compression bearing capacity of TCFDST members. The formulas commonly used at present for calculating the axial-compression bearing capacity of CFDST include: ACI 318–19 code [45], AISC 360–22 code [46], EC4 code [47], T/CCES 7–2020 code [48], and GB 50936–2014 code [49], among others. The specific expressions of the code formulas are shown in Eqs. (3)-(11), and Table 4 gives the predictive performance of five code formulas and four optimized models.

$$N_{\mathrm{u,ACI}} = f_{\mathrm{syo}} A_{\mathrm{so}} + 0.85 f_{\mathrm{c}} A_{\mathrm{c}} + f_{\mathrm{syi}} A_{\mathrm{si}} \tag{7}$$

$$N_{\mathrm{u,AISC}} = \begin{cases} N_{\mathrm{p}} \\ N_{\mathrm{p}} - \dfrac{N_{\mathrm{p}} - N_{\mathrm{y}}}{(\lambda_{\mathrm{r}} - \lambda_{\mathrm{p}})^2} (\lambda - \lambda_{\mathrm{p}})^2 + f_{\mathrm{syi}} A_{\mathrm{si}} \\ f_{\mathrm{cr}} A_{\mathrm{so}} + 0.70 f_{\mathrm{c}} A_{\mathrm{c}} + f_{\mathrm{syi}} A_{\mathrm{si}} \end{cases} \tag{8}$$

$$N_{\mathrm{u,EC4}} = \left(1 + \eta_{\mathrm{c}} \frac{t_{\mathrm{o}} f_{\mathrm{syo}}}{D_{\mathrm{o}} f_{\mathrm{c}}}\right) f_{\mathrm{c}} A_{\mathrm{c}} + \eta_{\mathrm{a}} \left(f_{\mathrm{syo}} A_{\mathrm{so}} + f_{\mathrm{syi}} A_{\mathrm{si}}\right) \tag{9}$$

$$N_{\mathrm{u,T/CCES}} = f_{\mathrm{scy}} \left(A_{\mathrm{so}} + A_{\mathrm{sc}}\right) + f_{\mathrm{syi}} A_{\mathrm{si}} \tag{10}$$

$$N_{\mathrm{u,GB}} = f_{\mathrm{sc}} A_{\mathrm{sc}} + f_{\mathrm{syi}} A_{\mathrm{si}} \tag{11}$$

Table 4 Comparison of evaluation metrics between design codes and heuristic-algorithm-optimized BPNN models

Code/model	$\varepsilon_{\mathrm{RMSE}}$	$\varepsilon_{\mathrm{MAE}}$	R^2	$\varepsilon_{\mathrm{MAPE}}$/
ACI 318–19	1 161.105	997.702	0.479	18.17
AISC 360–22	1 340.139	1 158.649	0.307	19.95

Code/model	$\varepsilon_{\text{RMSE}}$	ε_{MAE}	R^2	$\varepsilon_{\text{MAPE}}$/
EC4	608.397	540.668	0.857	11.39
T/CCES 7 –2020	473.692	366.799	0.913	7.10
GB 50936 –2014	1 204.306	1 071.743	0.440	19.17
BPNN	187.373	71.875	0.973	1.90
GA-BPNN	127.912	44.544	0.991	1.09
PSO-BPNN	147.580	47.832	0.994	1.12
SA-BPNN	100.595	43.768	0.996	1.13
ACO-BPNN	117.150	48.287	0.996	1.11

As shown in Fig. 11(a), the modified ACI 318–19 code formula treats the axial-compression bearing capacity of the member as the outer steel tube, inner steel tube, and sandwich concrete

contributing axial compressive bearing capacities, and, at the same time, uses a reduction factor to calculate the axial compressive bearing capacity contributed by the core concrete in a conservative manner; therefore, the calculated bearing capacity of the test set is lower than the measured value.

As shown in Fig. 11(b), the modified AISC 360–22 code formula treats the axial compressive bearing capacity of the member as the superposition of two parts: the inner steel tube and the outer steel tube-sandwich concrete. The superposed value obtained after applying reduction factors to the bearing capacities contributed separately by the outer steel tube and the sandwich concrete is taken as the bearing capacity of the composite section, and the confinement effect of the outer steel tube is considered only when calculating the buckling bearing capacity of the composite section. Therefore, the calculated bearing capacity of the test set is lower than the measured value.

As shown in Fig. 11(c), the modified EC4 code treats the axial compressive bearing capacity of the member as the superposition of the bearing capacities contributed by the sandwich concrete and by the outer steel tube-inner steel tube. It also considers the strength reduction effect of the outer steel tube-inner steel tube under composite loading and the strength enhancement effect of the sandwich concrete; therefore, the errors in the calculated bearing capacity of the test set are generally less than 20%.

As shown in Fig. 11(d), the T/CCES 7–2020 code treats the axial compressive bearing capacity as the superposition of the axial compressive bearing capacity contributed by the outer steel tube-sandwich concrete composite section and that contributed by the inner steel tube. Through parameters such as the steel ratio of the section, the nominal steel ratio, and the confinement coefficient, it accounts for the enhancement effect of the outer steel tube confinement on the strength of the sandwich concrete; therefore, the errors in the calculated bearing capacity of the test set are generally less than 20%.

As shown in Fig. 11(e), the modified GB 50936—2014 code treats the axial compressive bearing capacity as the superposition of the axial compressive bearing capacity contributed by the outer steel tube-sandwich concrete composite section and that contributed by the inner steel tube. The axial compressive bearing capacity of the composite section is calculated as the product of the composite compressive strength of the section and the converted section area; therefore, the errors in the calculated bearing capacity of the test set are generally smaller than the predicted values.

As shown in Fig. 11(f)–Fig. 11(i) and Fig. 12, the predicted axial compressive bearing capacities obtained from the four BPNN models optimized by heuristic algorithms have higher fitting accuracy than those obtained from the code formulas. Moreover, compared with the BPNN model, their prediction performance on both the training set and the test set is improved to a considerable extent, and all error indices are better.

Fig. 11 Graph of predicted–actual bearing capacity relationships obtained from specifications and heuristic-algorithm-optimized BPNN models

Subfigures:
(a) ACI 318—19; (b) AISC 360—22; (c) EC4; (d) T/CCES 7—2020; (e) GB 50936—2014; (f) GA-BPNN; (g) PSO-BPNN; (h) SA-BPNN; (i) ACO-BPNN.

Axes in each subfigure: horizontal axis, axial compressive bearing capacity (observed value)/kN; vertical axis, axial compressive bearing capacity (predicted value)/kN. Reference lines: $y = x$, $y = x \pm 10\%$, and $y = x \pm 20\%$.

Fig. 12 Residual plots of the training and testing sets for the BPNN model optimized by multiple heuristic algorithms

- (a) Residual plot for the GA-BPNN training and testing sets. Legends: BPNN—training set; GA-BPNN—training set; BPNN—testing set; GA-BPNN—testing set. Axes: residual/kN; number of samples.
- (b) Residual plot for the PSO-BPNN training and testing sets. Legends: BPNN—training set; PSO-BPNN—training set; BPNN—testing set; PSO-BPNN—testing set. Axes: residual/kN; number of samples.
- (c) Residual plot for the SA-BPNN training and testing sets. Legends: BPNN—training set; SA-BPNN—training set; BPNN—testing set; SA-BPNN—testing set. Axes: residual/kN; number of samples.
- (d) Residual plot for the ACO-BPNN training and testing sets. Legends: BPNN—training set; ACO-BPNN—training set; BPNN—testing set; ACO-BPNN—testing set. Axes: residual/kN; number of samples.

5 Prediction Model Parametric Analysis

Because machine-learning algorithms construct complex implicit nonlinear mapping relationships between input and output parameters, it is not possible to intuitively analyze the variable–bearing-capacity relationships established by the prediction models. Therefore, an interpolation method was used to establish test sets with a single variable as the control parameter, and the single-variable-bearing-capacity variation curves were plotted according to the prediction models.

As shown in Fig. 13(a), when the hollow ratio of the bottom section is kept unchanged, increasing the bottom-section diameter of the outer steel tube, D_{ob}, causes the axial compressive bearing capacity of the test samples to exhibit an increasing trend. This is because the increase in the bottom diameter of the member reduces the slenderness ratio and enlarges the effective compressed cross-section. The four prediction models fit well with the increasing trend of the member bearing capacity. The code formula conservatively calculates the bearing capacity of the member using the minimum cross-section at the top, and corrects the calculated length of the member through the taper formula. As the bottom diameter increases, the calculated length of the member decreases; consequently, the predicted bearing capacity increases with increasing D_{ob}.

As shown in Fig. 13(b), when the hollow ratio of the top section of the member is kept unchanged, increasing the top-section diameter of the outer steel tube, D_{ot}, causes the axial compressive bearing capacity of the test samples to exhibit an increasing trend. This is because the enlargement of the effective compressed cross-section of the member plays a dominant role in influencing the member bearing capacity. The four prediction models and the code formula all show an increasing trend.

As shown in Figs. 13(c) and 13(d), when the taper of the member is kept unchanged, increasing the bottom diameter of the inner steel tube, D_{ib}, or the top diameter of the inner steel tube, D_{it}, causes the axial compressive load of the test samples to exhibit a decreasing trend. This is because the hollow ratio of the member section increases as the diameter of the inner steel tube (top or bottom) increases, reducing the effective compressed area of the member. The four prediction models and the code formula reflect the same decreasing trend.

As shown in Figs. 13(e) and 13(f), when the wall thickness of the outer steel tube, t_{o}, or the wall thickness of the inner steel tube, t_{i}, is increased, the axial compressive bearing capacity of the test samples exhibits an increasing trend. This is because the effective compressed area of the outer (inner) steel tube increases and its confining effect on the sandwiched concrete is strengthened. The four prediction models and the code formula all show an increasing trend.

As shown in Fig. 13(g), as the height of the member increases, the axial compressive bearing capacity of the test samples continuously decreases. This is because the slenderness ratio of the member increases with height, the stability coefficient of the member decreases, and the bearing capacity is reduced. The four prediction models and the code formula all reflect the same decreasing trend.

Fig. 13 Parameter analysis of the BPNN model optimized by multiple heuristic algorithms
Fig. 13 Parameter study of multiple heuristic algorithms optimizing BPNN model

Visible plot annotations:

- **(a) Outer steel tube bottom diameter-axial compressive capacity (simulation)**
  x-axis: D_{ob}/mm; y-axis: axial load/kN.
  $D_{\mathrm{ot}} = 360$ mm, $t_o = 3.00$ mm, $f_{\mathrm{syo}} = 420.00$ MPa;
  $D_{\mathrm{it}} = 110$ mm, $t_i = 3.00$ mm, $f_{\mathrm{syi}} = 420.00$ MPa;
  $H = 1\,500$ mm, $f_c = 42.07$ MPa.
- **(b) Outer steel tube top diameter-axial compressive capacity** [18]
  x-axis: D_{ot}/mm; y-axis: axial load/kN.
  $D_{\mathrm{ot}} = 350$ mm, $t_o = 3.82$ mm, $f_{\mathrm{syo}} = 439.30$ MPa;
  $D_{\mathrm{ib}} = 231$ mm, $t_i = 2.92$ mm, $f_{\mathrm{syi}} = 396.50$ MPa;
  $H = 1\,050$ mm, $f_c = 44.39$ MPa.
- **(c) Inner steel tube bottom diameter-axial compressive capacity** [24]
  x-axis: D_{ib}/mm; y-axis: axial load/kN.
  $D_{\mathrm{ob}} = 158.00$ mm, $t_o = 1.50$ mm, $f_{\mathrm{syo}} = 308.00$ MPa;
  $D_{\mathrm{ot}} = 158.00$ mm, $t_i = 1.50$ mm, $f_{\mathrm{syi}} = 308.00$ MPa;
  $H = 450$ mm, $f_c = 18.70$ MPa.
- **(d) Inner steel tube top diameter-axial compressive capacity simulation**
  x-axis: D_{it}/mm; y-axis: axial load/kN.
  $D_{\mathrm{ob}} = 360$ mm, $t_o = 3.00$ mm, $f_{\mathrm{syo}} = 420.00$ MPa;
  $D_{\mathrm{ot}} = 360$ mm, $t_i = 3.00$ mm, $f_{\mathrm{syi}} = 420.00$ MPa;
  $H = 1\,000$ mm, $f_c = 42.07$ MPa.
- **(e) Outer steel tube thickness-axial compressive capacity** [32]
  x-axis: t_o/mm; y-axis: axial load/kN.
  $D_{\mathrm{ob}} = 114.30$ mm, $D_{\mathrm{ot}} = 114.30$ mm, $f_{\mathrm{syo}} = 438$ MPa;
  $D_{\mathrm{ib}} = 48.30$ mm, $D_{\mathrm{it}} = 48.30$ mm, $f_{\mathrm{syi}} = 425$ MPa;
  $t_i = 2.90$ mm, $H = 400$ mm, $f_c = 63.40$ MPa.
- **(f) Inner steel tube thickness-axial compressive capacity** [26]
  x-axis: t_i/mm; y-axis: axial load/kN.
  $D_{\mathrm{ob}} = 114.30$ mm, $D_{\mathrm{ot}} = 114.30$ mm, $f_{\mathrm{syo}} = 455$ MPa;
  $D_{\mathrm{ib}} = 60.30$ mm, $D_{\mathrm{it}} = 60.30$ mm, $f_{\mathrm{syi}} = 353$ MPa;
  $t_o = 5.85$ mm, $H = 345$ mm, $f_c = 38.34$ MPa.

- **(g) Specimen height-axial compressive capacity** [30]
  x-axis: H/mm; y-axis: axial load/kN.
  $D_{\text{ob}} = 139.20$ mm, $D_{\text{ot}} = 139.20$ mm, $f_{\text{syo}} = 418$ MPa;
  $D_{\text{ib}} = 76.00$ mm, $D_{\text{it}} = 76.00$ mm, $f_{\text{syi}} = 324$ MPa;
  $t_o = 3.00$ mm, $t_i = 3.00$ mm, $f_c = 27.72$ MPa.
- **(h) Sandwich concrete strength-axial compressive capacity (simulation)**
  x-axis: f_c/MPa; y-axis: axial load/kN.
  $D_{\text{ob}} = 386.67$ mm, $D_{\text{ot}} = 360.00$ mm, $f_{\text{syo}} = 355$ MPa;
  $D_{\text{ib}} = 311.67$ mm, $D_{\text{it}} = 285.00$ mm, $f_{\text{syi}} = 355$ MPa;
  $t_o = 3.00$ mm, $t_i = 3.00$ mm, $H = 1\,000$ mm.

Legend: GA-BPNN; PSO-BPNN; SA-BPNN; ACO-BPNN; ACI 318–19; AISC 360–22; EC4; T/CCES 7–2020; GB 50936–2014; TEST.

As shown in Fig. 13(h), as the strength of the sandwich concrete increases, the axial compressive capacity of the test specimens increases. This is because the increase in the sectional strength of the composite member raises the load-bearing capacity of the member. When the strength of the sandwich concrete continues to increase, however, the confining effect of the outer steel tube on it decreases, causing the increase in load-bearing capacity to gradually diminish. The four prediction models and the code formulas all agree well with the variation trend of the member capacity.

6 Conclusion

Based on the standard BP neural network model, heuristic algorithms were introduced to perform global and local optimization of the initial weights and thresholds of the BPNN. A BPNN prediction model for the axial compressive capacity of TCFDST members optimized by heuristic algorithms was proposed, and the following conclusions were obtained.

1) The established database takes member dimensions–including the bottom diameter of the outer steel tube, top diameter of the outer steel tube, wall thickness of the outer steel tube, bottom diameter of the inner steel tube, top diameter of the inner steel tube, wall thickness of the inner steel tube, and member length–and material strengths–including concrete strength, yield strength of the outer steel tube, and yield strength of the inner steel tube–as input parameters, with the axial compressive capacity of the member as the output variable.
2) The BPNN axial-compressive bearing-capacity prediction model optimized using four heuristic algorithms has smaller errors than machine-learning algorithms such as BPNN, RF, KNN, SVR, and RBFNN in all error indicators on the training set, validation set, and test set; after model optimization, the fitting performance on the test set is improved.
3) Compared with the code-based formulas, the BPNN prediction models

optimized by the four heuristic algorithms all show good accuracy in predicting axial-compressive bearing capacity on the training set, validation set, and test set: the goodness of fit is greater than 0.99, and the mean absolute percentage error is less than 2%.

4) The parametric analysis shows that the prediction model can effectively capture the variation pattern between the input variables and the axial-compressive bearing capacity. Compared with the axial-compressive bearing-capacity formulas proposed in the various codes, the bearing-capacity development curves of the prediction model under the key parameters have higher accuracy.

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