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# Rapid design for large-scale parallel CFRP cable with multi-source experimental data

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ABSTRACT

With advancements in material properties and reduced costs, carbon fibre reinforced polymer (CFRP) cables are gaining popularity in engineering applications due to their superior strength-to-mass ratio and durability. However, the tensile strength of large-scale parallel CFRP cables remains a critical issue, warranting further research and engineering expertise. To address this issue, this paper proposes a method to rapidly predict and adaptively correct the tensile strength of large-scale parallel CFRP cables using multi-source experimental data and an integrated approach that incorporates Monte Carlo simulations, Neural Network algorithms, and Genetic algorithms. This comprehensive method takes into account the influence of various factors including small-scale material strength and its coefficient of variation, cable length, the number of parallel wires, installation errors, and anchorage errors. Validated by reported experimental data, the method demonstrates its effectiveness in accurately predicting the tensile strength of parallel CFRP cables. Moreover, a design method for large-scale parallel CFRP cables is proposed based on the reliability theory. Lastly, the efficiency and effectiveness of the proposed method are validated through the design and optimization of a cable-stayed bridge featuring a main span of 1984 m, utilising both parallel steel and CFRP cables.

## 1. Introduction

FRP cables have numerous advantages including low density, high strength, corrosion resistance, and fatigue resistance. These exceptional attributes make CFRP a viable alternative to steel cables for cable manufacturing in cable-supported structures [1]. The potential of CFRP cables in large-span bridge construction was highlighted as early as 1986 by Meier [2], proposing the construction of a CFRP cable suspension bridge spanning 8400 m across the strait of Gibraltar. Later, parallel CFRP cables have become more common on pedestrian bridges [3-5]. These applications have led to investigations into related research such as anchoring systems [6-9], service life and economy [10,11], safety factors in cable design, and reliability design methods for structures [11,12], indicating that the strength and safety of CFRP cables have emerged as primary factors limiting engineering applications. In recent years, large-span structures have frequently necessitated the use of parallel CFRP tension cables, with growing demands in terms of length and cable force [6,10]. While there are methods available for predicting the strength of small-scale cables, the ability to predict the strength of large CFRP cables remains significantly limited [13].

In structural engineering, various types of CFRP cables are commonly used, including parallel bar cables, parallel plate cables, stranded cables, and self-anchored cables [14]. The investigation of fundamental material properties of CFRP is crucial, as the prediction of overall structural performance relies on a comprehensive understanding of the material's strength properties. Normal distribution [15,16] and Weibull distribution [17,18] are commonly used to describe the distribution of CFRP strength, and these studies have shown that both distributions can pass regression inspection. Moreover, similar materials and structural forms such as CFRP plates or GFRP bars have been extensively studied, providing comparable results in strength probability distribution modelling [19-21]. As the number of parallel wires increases, the Weibull distribution gradually converges to a normal distribution [22]. The weakest-link model [23] is most frequently applied to estimate the strength of longitudinal members, and the Weibull distribution is the most straightforward and practical

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mathematical model [24], although the normal distribution is also considered appropriate in some cases [25]. Various studies have highlighted differences in assumptions regarding different distribution patterns and analysed parameters [15,17,24].

Given that CFRP material is an elastic-brittle material, its strength is greatly influenced by the size effect [26,27]. In large-scale structures, the failure of a single element does not necessarily result in the overall failure of the structure [28]. When predicting the strength of large-scale parallel CFRP cables, the length and parallel coupling effects can be treated separately, as they are independent and do not interact with each other [29]. Some scholars [30,31] have taken a microscopic approach by simulating the damage of fibres and resins during the tensile process to establish strength prediction models from microscopic to macroscopic scales. However, these models are computationally expensive for large-scale CFRP cables. Additionally, due to technical limitations, it is challenging to experimentally determine a reliable strength distribution for small-scale materials [32]. Furthermore, these theories have limited applicability for large-scale elements, leading some researchers [33,34] to develop more complex predictive models. Zweben and Rosen [35] found that theoretical predictions correlated well with data from small-scale samples, they questioned the reliability of predictions for large-scale samples. Other research [33,36] has shown that certain models are only valid under specific size constraints. For a parallel cable composed of multiple wires, this study aims to determine a suitable distribution law for the strength of unit-length wire based on experimental data and to further predict the strength of large-scale cables.

To predict the strength of parallel CFRP cables, accurate unit-length wire strength is required as a basis for estimation. This can only be obtained through experimental or empirical means. To fully utilise test data with different specimen sizes and mitigate the influence of test conditions and size effects, a method of utilising multi-source experimental data is developed in this paper. The genetic algorithm [37] is well-suited for such problems, as it can search different regions of the solution space simultaneously and find discrete sets of solutions for nonconvex, discontinuous, and multimodal solution spaces [38]. The fitness function, a critical part of the genetic algorithm, should be chosen carefully. Maximum likelihood estimation (MLE) is commonly used for parameter estimation in civil engineering but weighted likelihood estimation (WLE) offers higher accuracy under complex conditions [39]. The Kolmogorov-Smirnov (K-S) test, which assesses the normal distribution using mean and variance values of the samples, is frequently used and has been modified by scholars [40]. Weber et al. [41] used minimized Kolmogorov-Smirnov estimation (MKSE) to estimate the best-fit distribution for given data. A fitness function with fast speed and good stability can be proposed for this study by combining these methods.

When designing steel tension cables, engineers generally rely on methods such as the allowable stress or limit state design method without considering the size effect [42]. However, the evident size effect of CFRP cables makes it challenging to control their strength using simple methods like the safety factor method, resulting in difficulties in structural design. For composite materials, many scholars [43-45] have conducted reliability analyses of structures or components using experimental data and Monte Carlo simulation. However, the Monte Carlo method is computationally inefficient and unsuitable for large-scale structural design and optimization. Machine learning (ML) has been extensively used in civil engineering for damage assessment and strength prediction, including material joints [46,47], failure modes of members [48,49], and structural performance [50].

ML algorithms can be categorized into supervised learning, unsupervised learning, and reinforcement learning, based on the dataset and learning approach [51]. In general, simple ML models with satisfactory accuracy are preferred over complex ones because they tend to generalize better to new data, require less raw data, and are more interpretable [52,53]. Commonly used methods for structural optimization include Kriging, Support Vector Regression (SVR), Polynomial Chaos Expansion (PCE) and neural network. Kriging is powerful in making predictions with small datasets and allows embedding domain knowledge in the prior [54]. However, it may yield poor predictions due to a bad choice of kernel and problems with hyperparameter optimization, and they do not scale well with big data. In SVR, the target is to establish a prediction equation with less than the allowed error based on the predicted output [55]. It has better robustness, but the selection of kernels and other hyperparameters can be complex [56]. The PCE method also requires preset setup parameters [57], which may not be effective for the high dimensionality and accuracy. For this study, the most widely used neural network is chosen as the acceleration algorithm, as it can meet the requirements of adjustability, accuracy, and computational speed simultaneously.

This study presents a prediction approach for enhancing the accuracy and speed of parallel CFRP cable strength using Monte Carlo estimation, Neural networks, and Genetic algorithm. The rest of the paper is organized as follows, and a detailed technical route is shown in Fig. 1. In Section 2, the factors influencing the strength of large-scale parallel CFRP cables composed of multiple wires are analysed. The theoretical calculation methods are proposed, and the estimation is implemented using the Monte Carlo method. To enhance the prediction accuracy, Section 3 utilises genetic algorithm and multi-source experimental data to estimate the strength of the most basic parameter, unit-length wire strength, during the prediction process. To improve computational speed, Section 4 reconstructs the prediction model using neural networks. Section 5 concludes this study and discusses the limitations of the proposed method.

## 2. Influencing factors of cable strength and Monte Carlo prediction

### 2.1. Theoretical prediction model

There are two main ways to identify the failure of a cable consisting of $n$ parallel wires [58]: one is that any one of the parallel wires breaks (serial model), and the other is when all of the parallel wires break (parallel model), as shown in Fig. 2. Assuming that the strength of a single wire $f_i$ ($i = 1, 2, 3, \ldots, n$) follows a normal distribution $f_i \sim N(u_0, \sigma_0)$, where $u_0$ is the mean and $\sigma_0$ is the standard deviation. For the serial model, the tensile strength of a cable containing $n$ parallel wires can be calculated as in Eq. (1). The distribution function of predicted strength using the serial model can be obtained by Eq. (2), where $P$ is the distribution function of predicted strength, and $\Phi$ is the cumulative distribution function of the standard normal distribution.

$$f = \min(f_1, f_2, f_3, \ldots, f_n) \tag{1}$$

$$P(x) = 1 - \left[1 - \Phi\left(\frac{x - u_0}{\sigma_0}\right)\right]^n \tag{2}$$

As for the parallel model, the tensile strength of a cable containing $n$ parallel wires can be calculated using Eq. (3), where $f_{\gamma 1}, f_{\gamma 2}, f_{\gamma 3}, \ldots, f_{\gamma n}$ are the actual tensile strengths of each single wire in descending order. The distribution function of the $k$-th order statistic $f_{\gamma k}$ can be calculated by Eq. (4). The distribution function of predicted strength using the parallel model can be obtained using Eq. (5).

$$f = \max\left[nf_{\gamma 1}, (n-1)f_{\gamma 2}, (n-2)f_{\gamma 3}, \ldots, f_{\gamma n}\right] / n \tag{3}$$

$$P_{f_{\gamma k}}(x) = \frac{n!}{(k-1)!(n-k)!} \int_0^{\Phi\left(\frac{x-u_0}{\sigma_0}\right)} t^{k-1}(1-t)^{n-k} dt \tag{4}$$

$$P(x) = \prod_{k=1}^{n} P_{\frac{n-k+1}{n} f_{\gamma k}}(x) = \prod_{k=1}^{n} \frac{n!}{(k-1)!(n-k)!} \int_0^{\Phi\left(\frac{\frac{n}{n-k+1}x - u_0}{\sigma_0}\right)} t^{k-1}(1-t)^{n-k} dt \tag{5}$$

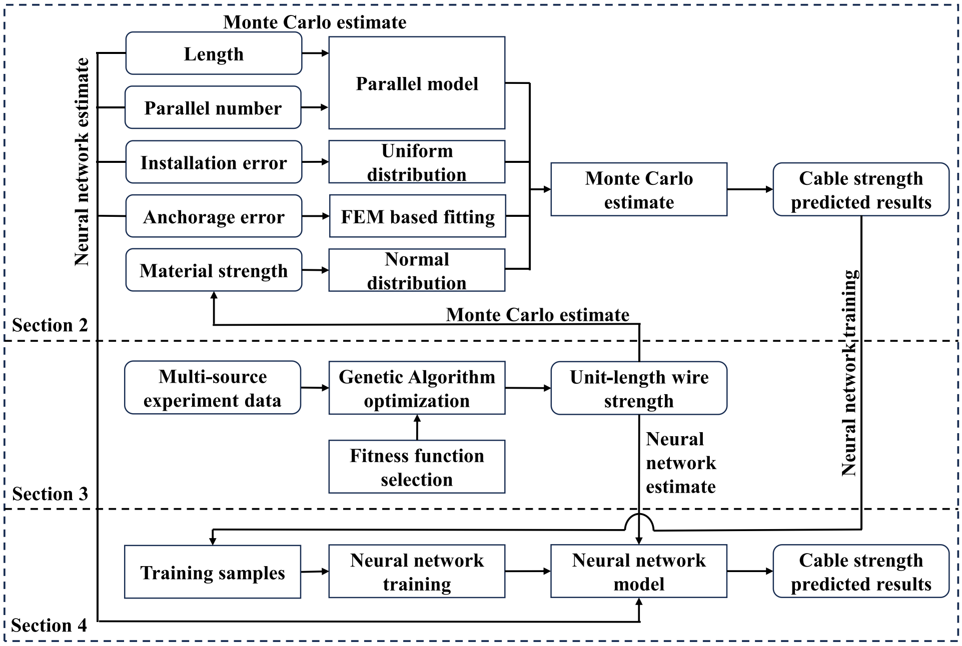



**Fig. 1.** Technical route for the rapid design of large-scale parallel CFRP cable.

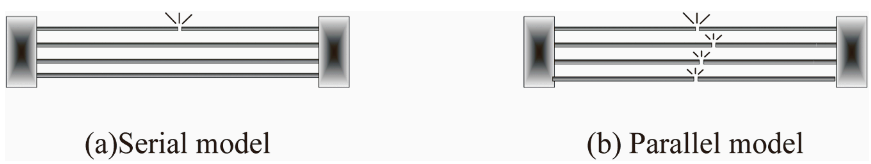



**Fig. 2.** Serial and parallel model failure modes.

The mean and standard deviation of the predicted tensile strength for both the serial and parallel models can be expressed as Eqs. (6) and (7), respectively.

$$u = \int_{+\infty}^{+\infty} x dP(x) \tag{6}$$

$$\sigma = \sqrt{\int_{+\infty}^{+\infty} (x-u)^2 dP(x)} \tag{7}$$

Fig. 3 illustrates the mean and characteristic values (95% guarantee) [59,60] of the predicted tensile strengths of parallel CFRP cables calculated by the two models. The mean and coefficient of variation of the unit-length wire strength are 2000 MPa and 0.02–0.06, respectively,

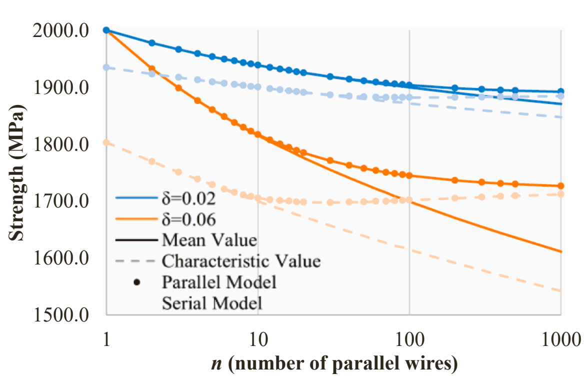



**Fig. 3.** Mean and characteristic values of the predicted strength of parallel CFRP cables.

and the coefficient of variation is the ratio of the standard deviation to the mean. The figure shows that the mean strength calculated by the serial model is significantly lower than that of the parallel model, and the difference in characteristic values become more significant as the number of parallel wires ($n$) increases. Therefore, the parallel model is employed in this study to predict the strength of large-scale cables, in line with the actual failure mode where the entire cable may not fail when the first wire breaks, especially in cables with a significant number of parallel wires.

### 2.2. *Influencing factors and estimation measures*

When estimating the strength of parallel CFRP cables, it is important to consider various influencing factors that may cause errors. Therefore, this study proposes a method for estimating the tensile strength of parallel CFRP cables based on the parallel model and the Monte Carlo method, taking into account factors such as mean and coefficient of variation of unit-length wire strength, cable length, number of parallel wires, and installation and anchorage errors.

A large-scale cable model (Fig. 4) is established based on the cable length and the number of parallel wires. A CFRP cable is divided into a parallel system of $n$ parallel wires, and each single wire is divided into several unit-length segments with different material strengths according

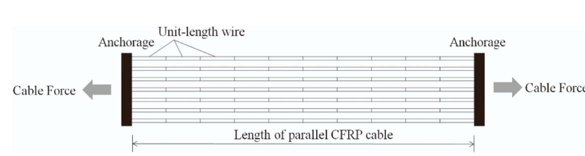



**Fig. 4.** Computational modelling of large-scale parallel CFRP cables.

to the mean and coefficient of variation of the unit-length wire strength.

The mean and coefficient of variation of the unit-length wire strength represent the strengths of a single wire of a pre-assumed unit length and can be determined through experiments or experience. The cable length can be expressed as the ratio of the total cable length ($L$) to the unit length ($l_0$). Using the parallel model and conducting Monte Carlo calculations, the results show the effect of the coefficient of variation of the unit-length wire strength, the cable length, and the number of parallel wires (Fig. 5 and Fig. 6). The shaded area represents the cable strength with a 99.7% guarantee. The cable strength decreases with increasing cable length, number of parallel wires, and coefficient of variation, respectively. Specifically, the cable strength experiences a decrease within the range of 0–1000 in cable length and 0–100 in the number of parallel wires, after which it stabilizes. Moreover, an increase in the coefficient of variation leads to a reduction in cable strength, further increasing the difference between the two models.

Due to the relative installation error between the parallel wires, the initial distribution of strength is not uniform, resulting in a reduction in cable tensile strength, as shown in Fig. 7. Chinese steel structure construction codes[61] require that the assembly gap of steel components should not be exceed than 2.0 mm. Based on this maximum limit, the effect of installation errors is estimated using Monte Carlo calculations, assuming a uniform distribution of errors and equal modulus of elasticity for all wires. Fig. 8 shows the reduction in cable tensile strength for different lengths ($l_0$ =280 mm) with 163 parallel wires and a coefficient of variation of unit-length wire strength of 0.01, under installation errors of a maximum of 0.5 mm and 1.0 mm. The shaded area represents the range of the 99.7% guarantee of the cable tensile strength. The effect of installation errors is significant for short cables but diminishes rapidly as the cable length increases. Considering the Chinese code's limit of a 2.0 mm assembly gap, this effect can be ignored for cables longer than 30 m, but should be considered for shorter cables.

Parallel CFRP cables are typically anchored using bonded or composite anchorage systems that rely on adhesive bonding or contact friction between materials to withstand axial forces [62]. When a cable is subjected to stress, each wire elongates, but deformation of the anchorage causes reduced elongation near the centre of the anchorage. This deformation systematically decreases the cable tensile strength and is referred to as anchorage error, as shown in Fig. 9. To analyse the anchorage deformation patterns of different layers, the difference in anchorage displacement generated by 91 CFRP parallel wires with a diameter of 5 mm anchored in epoxy adhesive was calculated using finite element analysis. A 1/12 model was used for calculation due to the symmetry, as shown in Fig. 10. The spacing of the CFRP wires was 2 mm, and the modulus of the epoxy adhesive was assumed to be 2 GPa. The outer surface of the epoxy adhesive was fixed, and a stress of 2000 MPa was applied to all wires.

To estimate the anchorage error of a parallel cable with any number

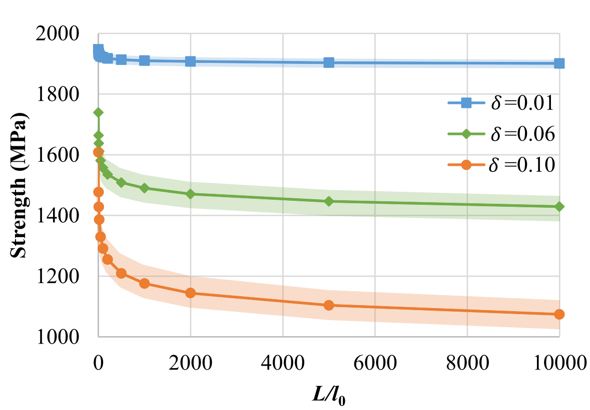



**Fig. 5.** Effect of cable length and coefficient of variation on cable strength ($n$ = 163).

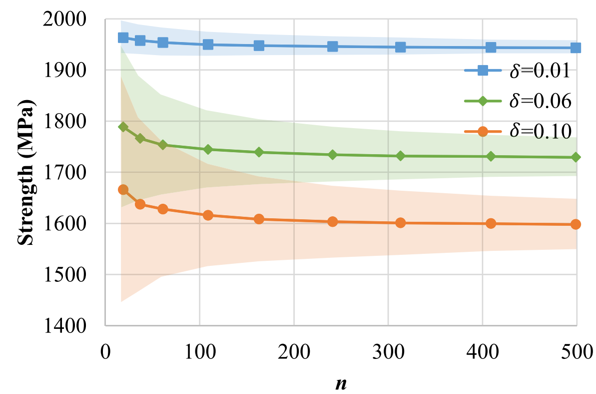



**Fig. 6.** Effect of number of parallel wires and coefficient of variation on cable strength ($L/l_0$ =1).

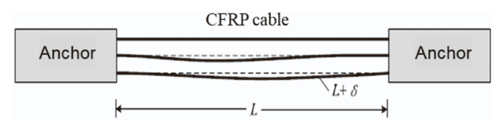



**Fig. 7.** Installation error for multiple wires.

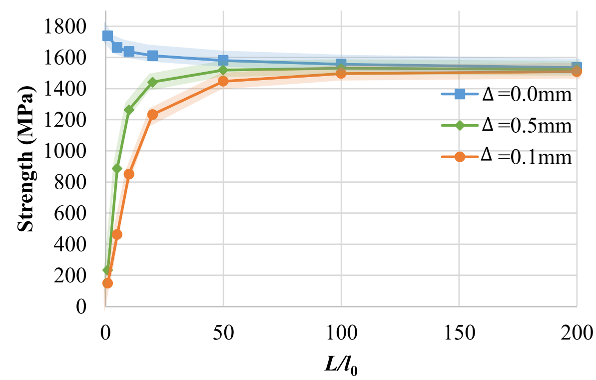



**Fig. 8.** Effect of installation error on cable strength.

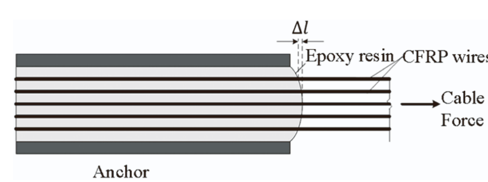



**Fig. 9.** Anchorage deformation under stress.

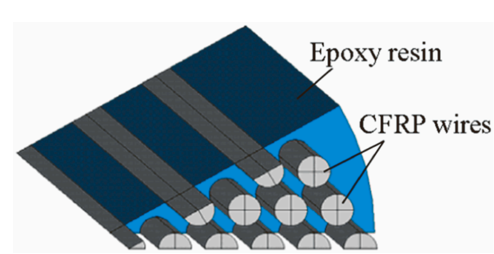



**Fig. 10.** 1/12 finite element modelling of anchor.

of parallel wires using only one given maximum displacement, the number of parallel wires $n_k$ corresponding to an integer number of layers $k$ is considered first for the case where the wires can be arranged in an ideal hexagonal arrangement (see Fig. 11). In the other case, the number of parallel wires is defined as $n = n_k + m$, where $m$ is the number of remaining wires in the outermost layer that cannot form an integer layer, and $m < n_{k+1} - n_k$. The number of layers is defined as $L = k + m/(n_{k+1} - n_k)$. Assuming cubic displacement curves for the different layers, where $y$ represents the displacement of wires in layer $x$, $L$ is the number of layers, and $\Delta l$ is the maximum displacement of the convex surface of the anchorage. This cubic equation should satisfy the boundary conditions $y(0) = 0$ and $y(L) = \Delta l$. Based on finite element analysis results and using the least squares method, the fitted equation is obtained as Eq. (8). The results are presented in Table 1.

$$y = \Delta l \bullet \left(0.7164\frac{x^3}{L^3} + 0.1484\frac{x^2}{L^2} + 0.1352\frac{x}{L}\right) \tag{8}$$

Monte Carlo calculations were performed 100,000 times by selecting different numbers of parallel wires and different maximum anchorage displacements $\Delta l$ (mean value of the unit-length wire strength: 2000 MPa, coefficient of variation: 0.005, cable length: 100 unit-length). The results are shown in Fig. 12. It can be observed that the cable tensile strength decreases with increasing maximum anchorage displacement and number of parallel wires, demonstrating good continuity for different numbers of parallel wires.

## 3. Optimal solution for unit-length wire strength with multi-source experimental data through genetic algorithms

### 3.1. Development of the genetic algorithm method

The cable tensile strength prediction methods mentioned previously require a known unit-length wire strength as a basis for estimation, which can only be obtained through experimentation or empirical data. To fully utilise the results of different test data with varied specimen sizes, a method using multi-source experimental data is developed. These multi-source experimental data refer to multiple test results of CFRP wires with the same material and diameter but different lengths, parallel numbers, and installation and anchorage errors. The total sample size of all tests should be at least two, otherwise the number of test data is less than the number of parameters and predictions will not be performed. The unit-length wire strength includes both the mean and coefficient of variation of the strength. The method for estimating the unit-length wire strength using genetic algorithms consists of four main steps and six sub-steps as follows, and the flowchart is shown in Fig. 13.

(1) Collect tensile strength test data for single or parallel cables with the same material and wire diameter.

(2) Define the unit length, which should be equal to or slightly less than the minimum test sample length.

(3) Assign different weights to different samples based on factors such as accuracy, reliability, repeatability, and size of the tested wires or cables in the multi-source test data.

(4) Estimate the mean and characteristic strengths of the unit-length wire that best fits the test data using genetic algorithms. This step further consists of six sub-steps:

① Select reasonable upper and lower limits for the unit-length wire

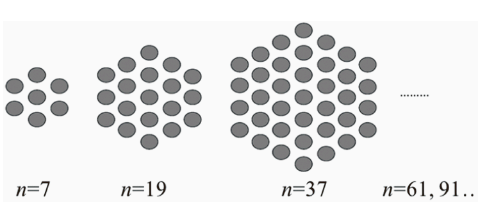



**Fig. 11.** Ideal hexagonal arrangement of wires.

**Table 1**
FEM and fitted displacements of the anchor.

| Layer | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| FEM (mm) | 0 | 0.04 | 0.14 | 0.34 | 0.64 | 1.14 |
| Fitted (mm) | 0.00 | 0.04 | 0.14 | 0.33 | 0.65 | 1.14 |

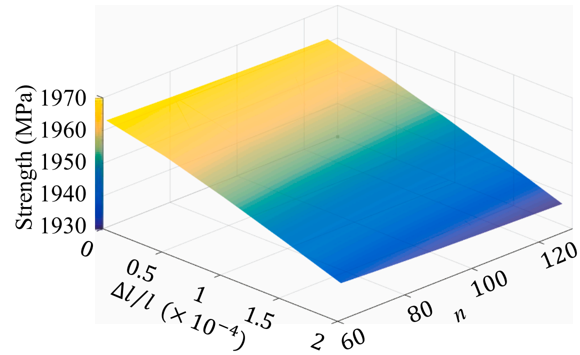



**Fig. 12.** Effect of anchorage error.

strength to restrain the searching range. Determine the maximum number of evolutionary generations $T$. Randomly generate $N$ individuals as the initial population $P(0)$. This method can use binary Gray coding for chromosome coding.

② Calculate the fitness value for each individual in the population $P(t)$ of the $t$-th generation. Three fitness functions are proposed to evaluate the fitness of the assumed unit-length cable strength based on available test data and artificially assigned weights.

A. Weighted likelihood estimation (WLE) fitness function.

The WLE fitness function is defined as follows: given a mean strength $\mu_0$ and coefficient of variation of the strength $\delta_0$, estimates of the mean and coefficient of variation of the strength for each test sample are calculated based on available test data and weights using Monte Carlo or neural network prediction (an alternative acceleration model in Section 4). After obtaining the strength distribution of each test sample separately, the maximum likelihood function is calculated using the probability density function of each sample as Eq. (9). An equivalent logarithmic function is chosen as the fitness function Eq. (10) with weights $k_i$ of test samples. A smaller value of this function indicates a better estimate of the initially assumed unit-length wire strength.

$$\text{lik}(\mu_0, \delta_0) = \prod p_i(T_i) \tag{9}$$

$$ef = -\sum k_i \ln(p_i(T_i)) \tag{10}$$

Maximum likelihood estimation is a commonly used method but is biased and prone to overfitting due to its disregard for interconnections between samples and reliance on pre-assumed distributions. Significant size differences among samples may lead to estimation errors and local optimum solutions.

B. Weighted Kolmogorov-Smirnov estimation (WKSE) fitness function.

This study introduces the WKSE fitness function, which considers the differences in the reliability of experimental data. The WKSE fitness function is defined as follows: given a mean strength $\mu_0$ and coefficient of variation of the strength $\delta_0$, estimates of the mean and coefficient of variation of the strength are calculated for each test sample based on available test data and weights using Monte Carlo or neural network prediction. The distribution law of the material strength for each test sample is obtained, and the offset of the test data is calculated using Eq. (11), where $T_i$ is the test value of the $i$-th test sample, $\mu_i$ and $\delta_i$ are the calculated mean and coefficient of variation of that test sample, respectively. The empirical distribution function for $\Delta_i$ is written as Eq.

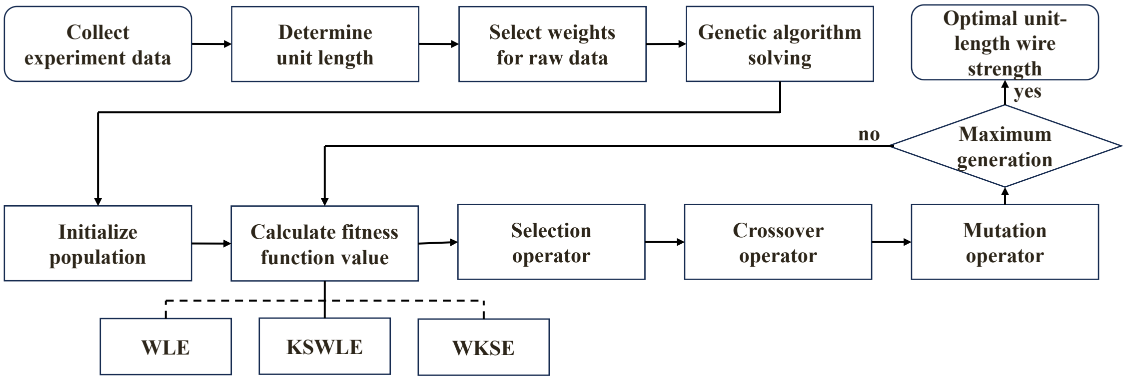



**Fig. 13.** Flowchart of genetic algorithm method.

(12), where $I_{[-\infty,x]}(\Delta_i)$ is defined as Eq. (13). The WKSE statistic $D$, which represents the largest difference in the distribution function, is calculated as Eq. (14), where $k_i$ is the weight of the $i$-th test sample, and $\Phi(x)$ is the distribution function of $x \sim N(0,1)$. A smaller value of this function indicates a better estimate of the initially assumed unit-length wire strength.

$$\Delta_i(\mu_0, \delta_0) = \frac{T_i - \mu_i}{\delta_i \mu_i} \tag{11}$$

$$F_n(x) = \frac{1}{\sum k_i} \sum_{i=1}^{n} \left(k_i \bullet I_{[-\infty,x]}(\Delta_i(\mu_0, \delta_0))\right) \tag{12}$$

$$I_{[-\infty,x]}(\Delta_i) = \begin{cases} 1, \Delta_i \le x \\ 0, \Delta_i > x \end{cases} \tag{13}$$

$$ef = D(\mu_0, \delta_0) = \max\left(\left|\Phi\left(\frac{x}{\sum k_i}\right) - F_n(x)\right|\right) \tag{14}$$

Unlike the WLE method, the WKSE method takes into account the relationship between data and evaluates the degree of closeness to a normal distribution. However, the WKSE statistic $D$ can be highly sensitive when the amount of test data is small, leading to significant errors.

C. Kolmogorov-Smirnov weighted likelihood estimation (KSWLE) fitness function.

To address these issues, a weighted maximum likelihood estimation method constrained by the Kolmogorov-Smirnov (K-S) test, called KSWLE, is proposed. The ideal K-S test statistic is defined as the expected value of the WKSE statistic $D$ calculated using Eq. (14) for $n$ normally distributed random variables $X_i \sim N(0,1)$ (see Eq. (15)). The modified maximum likelihood function is defined as Eq. (16), and the equivalent Eq. (17) is selected as the fitness function, incorporating the test sample weight parameter $k_i$. A smaller value of this function indicates a better estimate of the initially assumed unit-length wire strength.

$$\overline{D_n} = E\left\{\max\left[\left|\Phi\left(\frac{x}{\sum k_i}\right) - \frac{1}{\sum k_i}\sum_{i=1}^{n}\left(k_i \bullet I_{[-\infty,x]}(X_i(0,1))\right)\right|\right]\right\} \tag{15}$$

$$\mathrm{lik}_{D(\mu_0,\delta_0)} = \frac{\prod p_i(T_i)}{\max\left[\frac{D(\mu_0,\delta_0)}{\overline{D_n}}, 1\right]} \tag{16}$$

$$ef = -\frac{e^{\sum\{k_i \bullet \ln[p_i(T_i)]\}/\sum k_i}}{\max\left[\frac{D(\mu_0,\delta_0)}{\overline{D_n}}, 1\right]} \tag{17}$$

The KSWLE method utilises the K-S test statistic to accelerate the maximum likelihood estimation process while avoiding problems such as overfitting in WLE and sensitivity in WKSE, resulting in faster convergence speed and better stability.

③ Randomly select individuals from the population $P$(t) to be inherited in the next generation. The selection process follows the roulette selection method, where the likelihood of selection is proportional to the individual's fitness value, ensuring that individuals with higher fitness are more likely to be chosen.

④ Apply the crossover operator to the population. The crossover operator determines the crossover position and probability of the selected individuals' chromosomes.

⑤ Apply the mutation operator on the population. The variation operator determines the mutation probability at different locations within the chromosomes of each individual.

⑥ Terminate the evolution if the maximum number of evolutionary generations, $T$ is reached. Otherwise, iterate to the next generation. Output the most suitable individual from the final population, and obtain the final solution by decoding the chromosome of that individual.

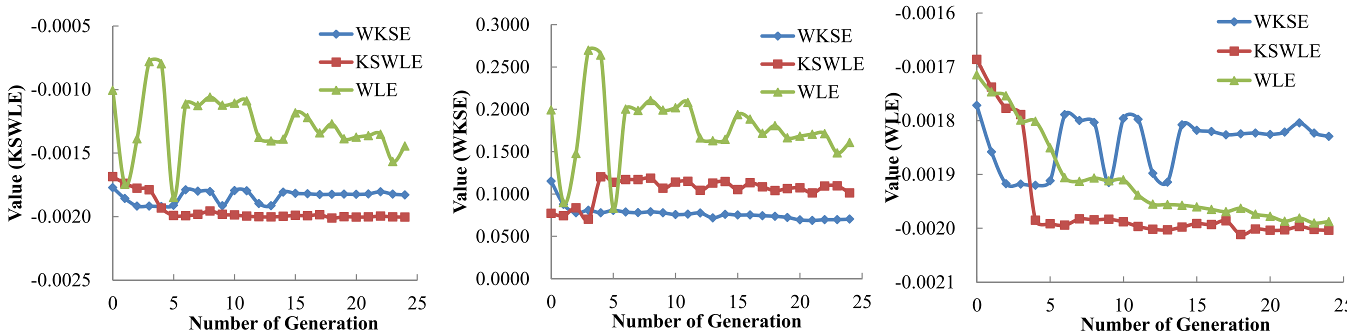
Using the genetic algorithm with the WLE, WKSE, and KSWLE fitness functions, the optimal solution is obtained using sample data from Case 2 (consisting of 43 samples). The population size is set to 48, and 24 generations are iterated. The values of WLE, WKSE, and KSWLE fitness functions for each generation in each method are calculated and shown in Fig. 14. The curves of different colours represent the three different methods, with Fig. 14 (a), (b), and (c) showing the KSWLE, WKSE, and WLE values of the optimal individuals in each generation for different fitness functions. From Fig. 14 (b) and (c), it can be observed that the WKSE method yields the best results for WKSE values but exhibits significant fluctuations in WLE values. The WLE method demonstrates the best convergence and results for WLE values but shows volatile WKSE values. Fig. 14 (a) indicates that the KSWLE method offers better convergence and stability. Fig. 14 (b) demonstrates that the KSWLE method is limited to a theoretical optimal WKSE value and seeks a better WLE value based on it. Fig. 14 (c) shows that the KSWLE method achieves faster convergence of WLE values compared to the MLE method, with similar final results. Consequently, the KSWLE method exhibits fast convergence speed, good stability, and can correct the biased MLE estimation restricted to the K-S test concerning sample size, making it suitable for solving the problem of multi-source test data in this study.

### *3.2. Results and discussions of unit-length wire strength prediction*

In the unit-length wire strength prediction process, the estimated strengths of carbon fibres (Case 1) and parallel CFRP cables (Case 2) are calculated using the proposed methodology and existing data to validate its performance.

**Case 1.** Tensile strength prediction for carbon fibres.

In this paper, the method described above for parallel CFRP cables was also investigated for its applicability to carbon fibres. The strength data of carbon fibres at 1, 10, 20, and 50 mm lengths obtained by Bader and Preist [63] and reported by Smith [64] were re-predicted.




(a) KSWLE value  (b) WKSE value  (c) WLE value

**Fig. 14.** The process of genetic algorithms for solving the unit-length wire strength under WLE, WKSE, and KSWLE fitness functions.

Predictions were performed using the modified Weibull estimation [18] method (data source: 1 +10 +20 +50 mm), the normal estimation method (data source: 1 mm), and four modified normal estimations with different data sources or weightings discussed in this study (data sources: 1 +10 mm, 1 +10 +20 mm, 1 +10 +20 +50 mm, and 1 +10 +20 +50 mm weighted by 1, 1, 1, and 2, respectively). Fig. 15 shows the specific experimental data and the results of different prediction methods for the strength of 50 mm long fibres. In this case, the "Modified Weibull" method represents the best available prediction method, "Normal" represents the result of the normal distribution method with only one data source, and "Modified Normal" represents the result of the normal distribution method with weighted four data sources. The shaded area in the figure indicates the prediction range with a 95% guarantee. It is evident that the results obtained through the "Modified Weibull" method are significantly better than those obtained through the "Normal" method, but not as good as the "Modified Normal" prediction.

Fig. 16 displays the overlapping probability between the test data and the predicted results (line graph) and characteristic strengths (bar graph) as primary parameters for engineering design. It can be observed that the accuracy of the ordinary normal prediction method is significantly lower than that of the modified Weibull prediction, indicating that the accuracy of normal prediction using a single data source is low. However, the modified normal prediction method, which employs more than two sets of multi-source data, surpasses the modified Weibull prediction. The accuracy of the modified normal prediction can be further improved with more data or the addition of weights. Prediction using more than three sets of data is deemed safe for engineering applications.

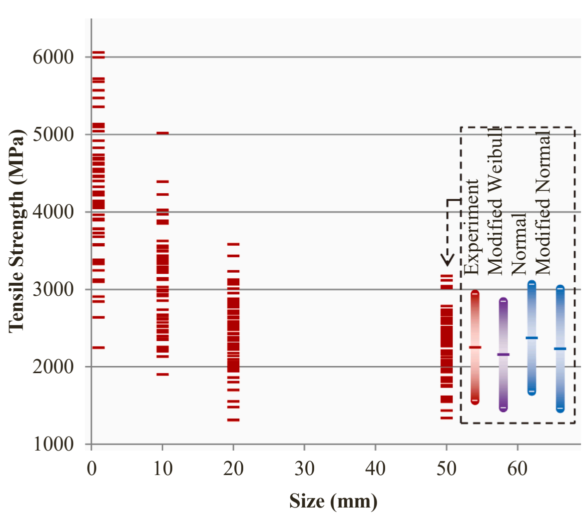



**Fig. 15.** Carbon fibres strength data [63,64] and the estimation results by different prediction methods.

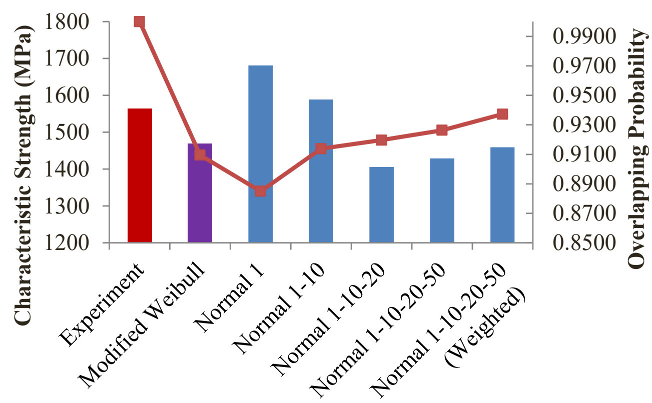



**Fig. 16.** Characteristic values (bar graph) and overlapping probability (line graph) by different prediction methods.

**Case 2.** Tensile strength prediction for parallel CFRP cables.

The strength data of 1, 4, 10 and 20 m long wires and 61 × 4 m parallel CFRP cables (each cable consisting of 61 parallel wires and measuring 4 m in length) were obtained from Lan et al. [18] for prediction purposes. Similar to Case 1, predictions were performed using the modified Weibull estimation [18] (data source: 1 +4 +10 +20 m), the normal estimation method (data source: 1 m), and four modified normal estimations with different data sources or weightings mentioned in this paper (data sources: 1 +4 mm, 1 +4 +10 m, 1 +4 +10 +20 m, and 1 +4 +10 +20 m weighted by 1, 1.25, 1.5, and 2, respectively). Fig. 17 illustrates the specific experimental data and the results of different prediction methods for the strength of 61 × 4 m parallel CFRP cables. As in Case 1, the "Modified Weibull" method represents the best prediction method, "Normal" represents the normal distribution method with only one data source, and "Modified Normal" represents the normal distribution method with weighted four data sources. The shaded area in the figure indicates the prediction range with a 95% guarantee. It can be observed that the "Modified Weibull" results are significantly better than the "Normal" results, but the "Modified Normal" prediction is remarkably close to the actual results.

Fig. 18 illustrates the overlapping probability between the test data and the predicted results (line graph) and characteristic strengths (bar graph) as primary parameters for engineering design. Similar to Case 1, the accuracy of the normal prediction method is significantly lower than that of the modified Weibull prediction, indicating the low accuracy of

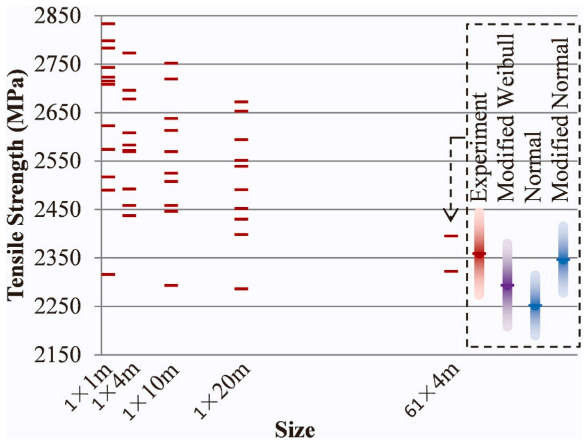



**Fig. 17.** CFRP wires and cables strength data [18] and the estimation results by different prediction methods.

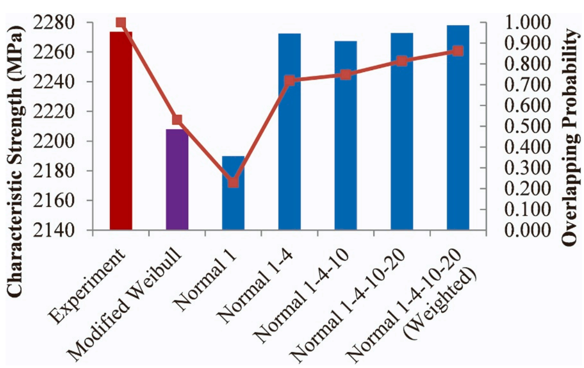



**Fig. 18.** Characteristic values (bar graph) and overlapping probability (line graph) by different prediction methods.

normal prediction using a single data source. However, the modified normal prediction method that incorporates more than two sets of multi-source data outperforms the modified Weibull prediction. The accuracy of the modified normal prediction can be further improved with more data or by adding weights. The characteristic strengths predicted using multi-source experimental data closely match the test results, making them suitable for engineering applications.

In this case, the accuracy of normal prediction using two data sets is higher, which may be attributed to the fact that the length of the target parallel CFRP cables aligns with the length of the second set of samples. This also demonstrates that incorporating high-quality test data can improve overall prediction accuracy, highlighting the scalability of this method.

It is important to note that the proposed fitness function in the genetic algorithm reduces the impact of poor test data. Nevertheless, if the test data error is significant, the solution may converge to a local optimum. Good test data and reasonable weights are essential, and human expertise is required for accurate prediction.

## 4. Speed and efficiency improvements of strength prediction through neural network

### *4.1. Establishment of neural network optimization method*

In the design of large structures like ultra-long span cable-stayed bridges, where the strength of large-scale parallel cables is a crucial part of the overall design, employing the Monte Carlo prediction method described earlier can significantly reduce the efficiency of design and optimization. As a solution, this section proposes an improved neural network prediction method that utilises the results obtained from the Monte Carlo prediction method.

Table 2 shows the range of values set for all independent dimensionless parameters of influencing factors. The independent dimensionless parameter for cable length is the ratio of cable length to unit length. Those for installation and anchorage errors are the ratios of the maximum error stresses to the mean strength of the unit-length wire. Within the range specified in Table 2, 1210 random samples were generated, with each sample subjected to Monte Carlo calculations 10,000 times to obtain the mean and characteristic values of cable tensile strength. Among the obtained samples, 1000 were selected as training samples for the neural network, 200 as validation samples, and ten as test samples. The neural network, as shown in Fig. 19, consists of five nodes in the input layer and two in the output layer. The input nodes correspond to the parameters in Table 2, while the output nodes represent the mean strength (MS) and characteristic strength (CS), equivalent to the mean strength and coefficient of variation, respectively. The intermediate layer contains two dense layers with activation functions of ReLU and linear, and they consist of 256 and 16 nodes, respectively. The learning parameters include 10,000 epochs, a batch size of eight, and a learning rate reduction of 20% every 1000 steps.

The neural network process is showed in Fig. 20. The mean error for the validation sample is 0.0010, satisfying the design accuracy requirement. The prediction errors for the mean and characteristic strengths of the test samples range from − 0.32% to 0.18% and from − 0.29% to 0.18%, respectively. This indicates that the neural network can provide better predictions for the tensile strength of parallel CFRP cables. With the proposed neural network trained using Monte Carlo results, it is now possible to estimate the tensile strength of parallel CFRP cables at any length, even if it does not correspond to an integer multiple of the unit length. This allows for rapid design in complex scenarios, such as optimizing structures with numerous extra-long cables, thus significantly improving optimization efficiency.

### *4.2. Results and discussions of the rapid design method for cable tension strength*

The assumption of normal distribution aligns better with the big data methodology employed in this paper than the Weibull distribution. To take multiple influencing factors into account, this method initially uses simulated data obtained through the Monte Carlo method and then accelerates the process using the neural network method. Acceptable results can be obtained without employing an overly complex neural network, with further optimization possible according to engineering requirements.

To demonstrate the application of this cable tensile strength prediction method in structural design, a 1984 m span cable-stayed bridge with hybrid steel and CFRP cables was selected as a design case. As shown in Fig. 21, the bridge has 112 pairs of cables in the midspan, with a horizontal cable spacing ranging from 16–20 m, a minimum cable inclination of 18.1°, and a tower height of 322.2 m above the deck. Among these cables, 52 pairs of cables near the middle of the span are parallel CFRP cables (blue lines in Fig. 21), and the remaining 60 pairs are steel cables. The steel cables comprise parallel steel wire cables with a strength of 1770 MPa, requiring a safety factor of no less than 2.7, and the number of steel cable types should be less than six. The main girder is

**Table 2**
Value range of each parameter.

| Parameters | Value range |
|---|---|
| Coefficient of variation for unit-length wire strength (COV) | 0–0.2 |
| Number of parallel wires ($n$) | 1–1000 |
| Cable length ($L/l_0$) | 1–10000 |
| Installation error (IE) | -0.025–0.025 |
| Anchorage error (AE) | 0–0.05 |

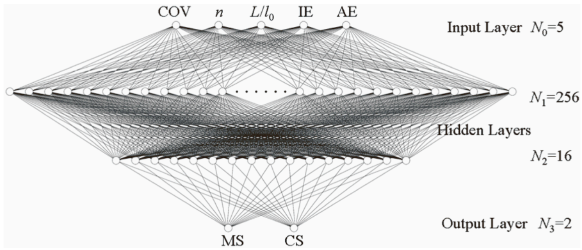



**Fig. 19.** The structure of the neural network built.

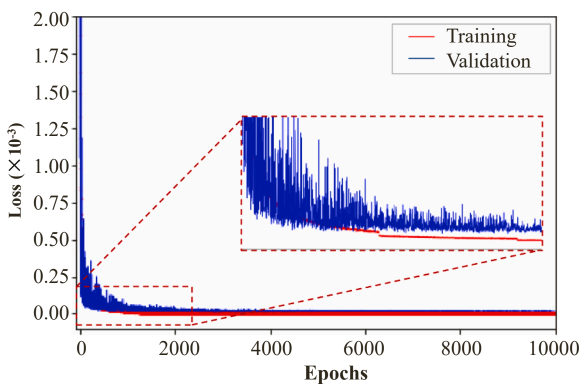



**Fig. 20.** Neural network learning progress.

made of Q370 steel with a elastic modulus of 206 GPa, a cross-sectional area of 2.302 m$^2$, and a bending moment of inertia of 8.605 m$^4$. The dead load of the bridge is 320 kN/m, and the live load follows a 4-lane load pattern according to the Chinese code [65].

Parallel CFRP cables have an elastic modulus of 160 GPa and no more than six cable diameter options. The unit-length wire strength is recalculated using the above CFRP wire/cable data. To maximize data utilisation, the initial data sets include 1 +4 +10 +20 m CFRP wire and 61 $\times$ 4 m CFRP cable data, with respective weights of 1, 1.25, 1.5, 2.0, and 4.0. The predefined search ranges for the mean and standard deviation of the unit-length strength are set as 2200–3400 MPa and 100–300 MPa, respectively, with a data accuracy of 0.1 MPa. The crossover probability is set at 0.9, and the variation probability is set as 1/chromosome length. There are 32 populations, each with 64 generations. After the algorithmic operation, 200,000 Monte Carlo predictions are used to calibrate the optimal result of each generation. The calculated mean strength of the unit-length wire is 2808.5 MPa, with a standard deviation of 177.2 MPa, slightly higher than the experimental data of 1 m CFRP wires, which confirms the unreliability of a single set of samples. Carbon fibre composites are brittle materials with limited design experience and related codes. The design of this case is based on the reliability theory of FRP material design [66,67]. There are only two independent variables, load and structural resistance, both of which follow a normal distribution, and the reliability index of the structure can be calculated using Eq. (18), where $\mu_S$ and $\sigma_S$ are the mean and standard deviation of loads; $\mu_R$ and $\sigma_R$ are the mean and standard deviation of the structural resistances.

$$\beta = \frac{\mu_R - \mu_S}{\sqrt{\sigma_R^2 + \sigma_S^2}} \tag{18}$$

According to the Chinese code [68], the reliability index of brittle materials for parallel CFRP cables should be at least 5.2. Considering the existing research [69], the reliability index of parallel CFRP cables should be higher, and in this case, it was set at 18. The safety coefficient (for steel cables) and reliability index (for CFRP cables) in this paper only consider the main dead and live loads, with a certain margin reserved for other loads. The coefficients of variation for the constant and live load cable force were adopted as 0.05 and 0.45 [69], respectively. The strength prediction of the parallel CFRP cable required for the design case is carried out through the neural network method, and the calculations are repeated several times during structural optimization. After optimization, the safety coefficient, reliability index, cable size, and cable force of the 1/2 midspan cable are obtained as shown in Fig. 22. The values of the cable force in Fig. 22 are differentiated by colour, with the bending moment of the bridge shown at the girder position. The design cable force varies uniformly, indicating good structural performance. Therefore, the parallel CFRP cable design method proposed in this paper is suitable for structural cable design.

In general, Fig. 22 demonstrates a high level of design for a cable-stayed bridge that surpasses the currently known maximum span. The transition between steel and CFRP cables is smooth in terms of structural performance, with the allowable stress of parallel CFRP cables decreasing gradually with increasing cable length. Conventional design methods may result in an unsafe design of CFRP cables, whereas this rapid design method can consider parallel CFRP cable force reduction by conveniently adding programming over many iterations and optimizations. An automatic cable size and force optimization program assisted in the design of the cable-stayed bridge in this case, although it is beyond the scope of this paper and does not affect the conclusions.

## 5. Discussions and conclusions

This study proposes a method to rapidly predict and adaptively correct the tensile strength of large-scale parallel CFRP cables using multi-source experimental data and an integrated approach that incorporates Monte Carlo simulations, Neural Network algorithms, and Genetic algorithms.

Main factors that affect the tensile strength of parallel CFRP cables are investigated, using the Monte Carlo method, incorporating the parallel force model and the normal distribution law of material properties. It is found that the cable strength is significantly reduced with the increase in cable length, number of parallel wires, and material coefficient of variation. Furthermore, the strength of short cables is also decreased by anchorage and installation errors.

To obtain the basic prediction parameter, the unit-length wire strength, a genetic algorithm method is proposed. This method utilises multiple sources of test data simultaneously. Additionally, a new KSWLE fitness function is introduced to address overfitting issues, leading to faster convergence, better stability, and improved extensibility. The genetic algorithm method minimizes the influence of experimental conditions and size effects, resulting in enhanced prediction confidence.

To enhance its usability, a neural network prediction model is established based on the samples generated through Monte Carlo

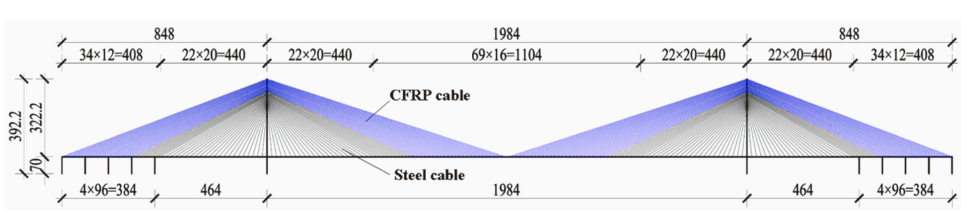



**Fig. 21.** Layout of the case bridge (m).

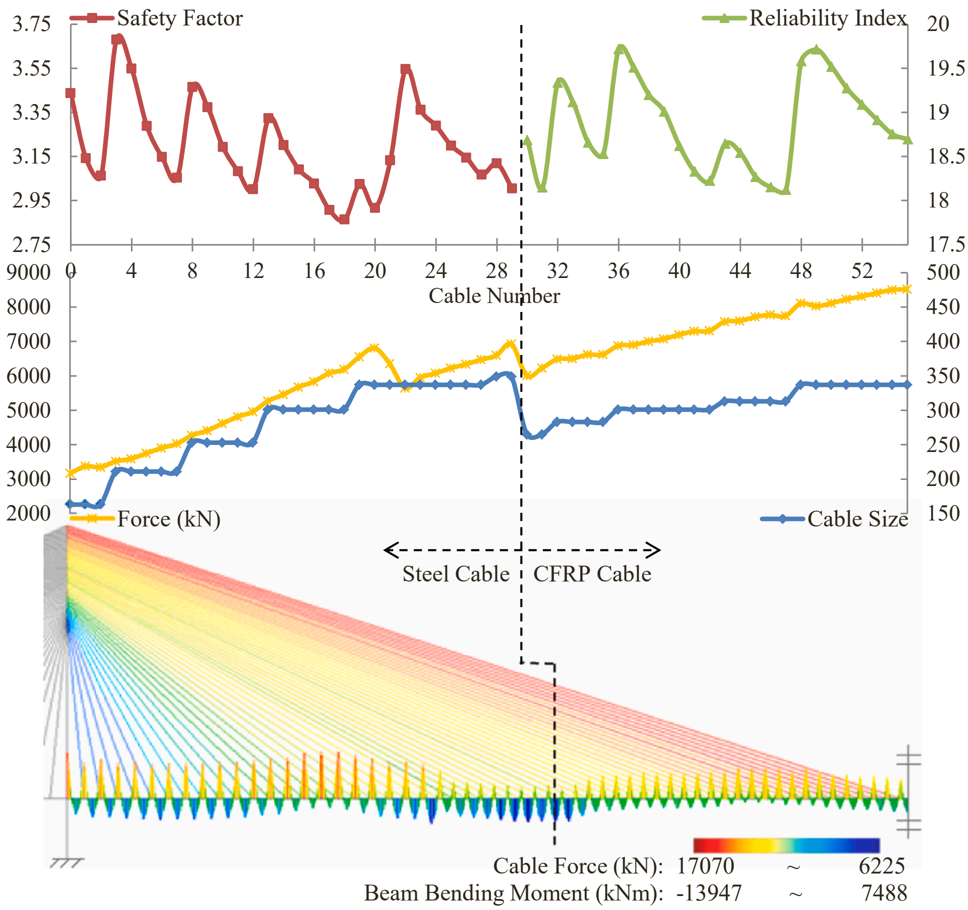



**Fig. 22.** Optimization results for the case cable-stayed bridge.

calculations. This neural network prediction expands the applicability of the method and significantly improves the speed of large-scale cable strength estimation. Building upon this accelerated approach, a reliability-based design method is developed for large-scale parallel CFRP cables in large structures. Ultimately, the rapid design method demonstrates excellent performance in the design of an ultra-long span cable-stayed bridge.

The method proposed in this study can enhance the efficiency of utilising experimental data and progressively improve prediction accuracy with increasing data volume. To improve prediction accuracy, it is crucial to conduct pre-checks on the experimental data and assign appropriate weights to data of varying sizes. Additionally, the scarcity of experimental data due to the challenge of testing large-scale CFRP cables poses a limitation. Therefore, it is necessary to validate the design method proposed in this paper through experimentation. Furthermore, extensive research is required to thoroughly investigate the reliability-based design method, particularly concerning the probability of structural loads. Lastly, although this method allows for rapid design, further investigation is needed to formulate simplified formulas that can be assimilated into standards and offer more direct design guidance.

## CRediT authorship contribution statement

**Chi Lu:** Methodology, Writing – review & editing. **Peng Feng:** Conceptualization, Project administration, Supervision, Writing – review & editing. **Guozhen Ding:** Formal analysis, Validation. **Pan Zhang:** Data curation, Formal analysis. **Li Dong:** Data curation, Formal analysis, Methodology, Writing – original draft.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data Availability

Data will be made available on request.

## Acknowledgments

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