Improved population initialization method and its application in bridge optimization

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Abstract. When solving bridge optimization problems by traditional genetic algorithms, a random method is often used to generate the initial population, which can’t ensure that the initial population is evenly distributed in the solution space and reasonably represents the solution space. In order to solve the shortcomings of random method, an improved population initialization method is proposed by combining random method with good point set. Based on it, aimed at the characteristic of implicit non-linear objective function or constraint function in bridge structure optimization, a BP neural network is used to simulate the relations between the objective function or constraint function and design variables. Then this paper takes a steel truss bridge as an example of optimization. Taken the allowable deflection of bridges as limit and aiming at minimizing the amount of steel, optimization model of bridge is established. Finally, the improved population initialization method is applied to solve the optimization model. The results show that the improved population initialization method can not only improve the uniformity of the population, but also be suitable for optimization design of bridges.

1. Introduction
When genetic algorithm is used to solve bridge optimization problems, stochastic method is often used to generate initial population [1-3]. The stochastic method can not ensure the uniform distribution of the initial population and reasonably represent the solution space [4]. When the initial population distribution is unreasonable or biased to one side of the solution space, the genetic algorithm may converge to the local optimal solution [5]. In addition, there are many variables in the optimization design of bridge structure, and the objective function or constraint function are implicit non-linear functions, which are mainly calculated by finite element simulation. However, in bridge optimization analysis, the objective function or constraint function values need to be calculated repeatedly and many times. It is not realistic to use finite element method alone.

In view of the shortcomings of genetic algorithm in solving bridge optimization problems, an improved population initialization method is proposed by combining stochastic method with good point set. Based on this, the objective and constraints of bridge optimization are determined, the optimization model of bridge is constructed. The implicit function of bridge is fitted by BP neural network [6]. And the improved population initialization method is applied to optimize the design of bridge structure.

2. Improved initial population method
The construction of good point set is simple, and the point selection is uniform in euclidean space with
small deviation [7]. The uniformity of initial population can be improved by good point set. The population is deterministic, lacking randomness when simply constructing the initial population with a set of good points. And that can not produce as many excellent individuals as possible close to the global optimal solution. Therefore, the strategy of combining random method with good point set is adopted to generate initial population. Some populations are generated by good point set to ensure that most of populations are evenly dispersed in the solution space, while others are generated by random method. The basic process is as follows:

1. Determine the number of initialized populations \( M \). \( M \) usually takes 20~100[8]. The solution accuracy of optimization problem increases with the increase of initial population [9]. The value of recommendation \( M \) is 100

2. Determine the number of populations generated by a good set of points. In order to ensure the uniformity of most populations, it is recommended to take values in the (0.5,1) interval. First, construct a good point set according to formula (1) [10].

\[
P_{sM,j} = \{r_j \times t\} \quad (i = 1, 2, \ldots, kM, j = 1, 2, \ldots, s)
\]

In the formula: \( r_j \) is the fractional part of \( e_j \); \( s \) as the number of design variables to be optimized

3. Generate a partial population through a good point set.

\[
X_{kM,s} = (X_{max} - X_{min}) \times P_{sM,j} + X_{min}
\]

In the formula: \( X_{max} \) the upper limit of the design variable; \( X_{min} \) the lower limit of the design variable.

4. The remaining population \((1 - k)M\) is generated by a random method.

\[
X_{(1-k)M} = (X_{max} - X_{min}) \times Rand_{(1-k)M} + X_{min}
\]

Start

Determine the initial population: \( M \)

Select the scale factor: \( k \)

Construct a good point set: \( P_{sM,j} \)

Generating partial populations through good point sets: \( kM \)

Construct a random point set: \( Rand_{(1-k)M} \)

Generate a residual population using a random point set \((1-k)M\)

End

Figure 1. Improved population initialization method

3. Bridge structure optimization model

Bridge structural optimization is usually constrained by displacement or stress. The bridge deflection function is mostly implicit non-linear function. It is inefficient to obtain the bridge deflection value by structural simulation when optimizing the structure design. In order to solve this problem, BP neural network is used to simulate this functional relationship. A large number of sample data are efficiently
obtained by finite element calculation of bridges. And the fitting accuracy is guaranteed by training samples. In theory, BP neural network can map all functions [11]. Based on this, taking a steel truss bridge as an example, the section area of chord as design variable, the allowable deflection as constraint, and the minimum amount of steel as objective, the optimization model of a steel truss bridge is constructed, as shown in Formula (4).

\[
\begin{align*}
\text{Find } & \quad X = [X_1, X_2, \ldots, X_m] \\
\text{Min } & \quad W(X) = \sum_{i=1}^{m} \rho_i X_i \\
\text{S.t } & \quad \omega \leq [\omega] \\
& \quad X_i^L \leq X_i \leq X_i^U (i = 1, 2, \ldots, m)
\end{align*}
\] (4)

In the formula: \( X \) as design variables; \( W(X) \) as objective function (taking steel quantity); \( \rho \) as the corresponding coefficient of the \( i \) design variable; \( \omega \) and \([\omega]\) as midspan deflection and allowable deflection respectively, the deflection value of the bridge is predicted by the trained BP neural network and the allowable deflection value of the bridge is calculated according to the code; \( X_i^L \) and \( X_i^U \) as the upper and lower limits of the \( i \) design variable respectively.

4. Optimal analysis of a steel truss bridge

4.1. Project overview

A 108m simple supported steel truss bridge is selected as an application example. According to the design information, the simulation model is built by ANSYS finite element analysis software (as shown in Figure 2).

![Figure 2. Finite element model of a steel truss bridge](image)

4.2. Optimal parameter

The structural optimization analysis of steel truss bridge under normal service limit state is carried out. The initial design variables are shown in Table 1. According to the Code for Design of Highway Steel Bridges (JTGD64-2015), the maximum allowable deflection of steel truss bridges is:

\[
[\omega] = \frac{L}{500} = \frac{108}{500} = 0.216 \text{m}
\]

| Table 1. Initial design variable table |
|----------------------------------------|
| Rod type | Section type | Area \( A \times 10^{-2} \) / m² |
| a       |              | 5.28                          |
| A2      |              | 4.35                          |
| A3      |              | 6.63                          |
| A4      |              | 7.99                          |
| A5      |              | 8.41                          |

A three-layer BP neural network is used to simulate the nonlinear relationship between bridge deflection and design variables. The logig function is used as the implicit layer transfer function. The pure-line function is used as the transfer function of the output layer. The input layer has 5 units and outputs. The layer has 1 unit, and the number of hidden layer units is determined by equation (5) [12], which is initially set to 12:
In the formula: \( M = \sqrt{n+m+a} \) 

In the formula: \( m \) and \( n \) are the number of neurons in the output layer and the input layer, respectively, \( a \) is a constant between \([0, 10]\).

200 design samples with uniform distribution are generated by good point set. The deflection of each sample is obtained by finite element analysis. After normalization of the sample [13], the network training is carried out to improve the generalization ability of the neural network. From Figure 3 and Figure 4, it can be found that BP neural network has a good effect in fitting bridge deflection. The maximum absolute error between the predicted value and the actual value is 0.0000799, and the maximum relative error is 0.000529, which can meet the requirements of structural optimization accuracy.

![Figure 3](image1.png)

**Figure 3.** Comparison between predicted value of BP neural network and actual value

![Figure 4](image2.png)

**Figure 4.** Fitting relative error of BP neural network

When using the improved population initialization method to optimize bridge design, decimal coding population is adopted to avoid mapping error caused by binary coding [14-15]. The population...
size is taken as 100, the scale factor $k$ is taken as 0.8, the genetic algorithm crossover probability is taken as 0.6, the mutation probability is taken as 0.15, and the design variable variation range is temporarily taken: $A1 \in [0.0502,0.0554]$, $A2 \in [0.0412,0.0457]$ $A3 \in [0.0630,0.0696]$, $A4 \in [0.0759,0.0839]$ $A5 \in [0.0799,0.0883]$

### 4.3. Optimized Results

The optimized design variables are shown in Table 2. The iterative process is shown in Figure 5. The actual deflection of the bridge is 0.152m. The predicted value of the neural network is 0.151. So the prediction error is small. Besides, the optimized chord steel consumption is 4.6% compared with the initial design. The method in this paper realizes the optimization design of steel bridge structure efficiently.

| Rod type | Section type | Area $A \times 10^{-2}$ / m² |
|----------|--------------|-----------------------------|
| $A1$     |              | 5.03                        |
| $A2$     |              | 4.14                        |
| $A3$     |              | 6.31                        |
| $A4$     |              | 7.60                        |
| $A5$     |              | 8.00                        |

![Steel consumption](image)

Figure 5. Iteration process of optimizing

### 5. Conclusions

(1) Combining good point set with random method, an improved population initialization method is proposed, which can effectively improve the uniformity and rationality of initial population distribution.

(2) The improved population initialization method is used to optimize the bridge design. After 60 population evolution, the objective function has been stable and convergent, and the steel consumption of the optimized chord is 4.6% less than that of the initial design. It shows that the improved method is suitable for solving the optimization problem of bridge structure.

(3) The deflection of the optimized bridge is 0.152 m, less than the allowable deflection 0.216 m, which meets the requirements of the code; and the optimized design variables approximate the lower
limit of the variable range, which shows that the improved method can achieve global optimization in the space of structural optimization design.

(4) Using good point set can efficiently generate uniformly distributed training samples of neural networks.

(5) The deviation between the bridge deflection value predicted by BP neural network and the actual value is very small, which indicates that BP neural network has a certain application prospect in bridge structure simulation calculation and structure optimization.

References

[1] Wu Xiaoguang, Feng Qi, Guo Yang. Limited optimization of bridge construction resources based on genetic algorithm [J]. Journal of Chang'an University (Natural Science Edition), 2004 (06): 33-36.

[2] Liu Wei, Wu Chunli, Wang Jing. Application of parthenogenetic genetic algorithm in optimizing sensor placement of bridges [J]. China-Foreign Highway, 2012, 32 (01): 195-198.

[3] Wang Shuangjie, Feng Qi. Research on resource balance optimization of bridge construction based on genetic algorithm [J]. Bridge construction, 2004 (02): 16-19.

[4] Xu Peng, Wang Lei, Zhang Wenyi. Improvement of population initialization for solving VRP by genetic algorithm [J]. Journal of Nanjing Normal University (Engineering Edition), 2009, 9 (03): 70-74.

[5] Tang Shihao, Zhu Qijiang. The influence of initial population and crossover, mutation rate on solution in genetic algorithm and its solution [J]. Science and Technology Bulletin, 2001 (03): 1-7.

[6] Lin Guangping, Huang Wei, Fang Mosheng, Liu Zhenqing. Multi-objective structural optimization design of orthotropic steel bridge deck system based on BP neural network [J]. Highway transportation science and technology, 2005 (05): 83-86.

[7] Hua Luogeng and Wang Yuan, Application of Number Theory in Approximate Analysis [M], Science Press, Beijing, 1978.

[8] Zhou Ming, Sun Shudong. Principle and Application of Genetic Algorithms [M]. Beijing: National Defense Industry Publication, 2000.23-25.

[9] Li Gang, Xue Huifeng, Xing Shubao. Functional relationship between the accuracy of genetic algorithm and population size [J]. Computer technology and development, 2006 (07): 96-98.

[10] Sun Jiaze, Wang Gang. White-box test case prioritization using good-point set genetic algorithm [J]. Computer Engineering and Science, 2018, 40 (10): 1815-1821.

[11] Vanderplaats G N. Structural Design Optimization Status and Direction [R]. AIAA 97-1407.

[12] Wang Xiaochuan. An analysis of 43 cases of MATLAB neural network [M]. Xi'an: Xi'an University of Electronic Science and Technology Press, 2002.

[13] Xu Dong, Wu Zheng, System analysis and design based on MATLAB 6.X - Neural Network [M]. Xi'an: Xi'an University of Electronic Science and Technology Press, 2002.

[14] Zheng Xiufen, Wu Guozhong. Development of decimal genetic algorithm and its simulation software [J]. Computer simulation, 2005 (01): 194-196.

[15] Han Ruifeng, Zhang Yongkui. An improved real-coded genetic algorithm [J]. Computer Engineering and Application, 2002 (13): 78-80.