

Cost Optimization of Steel Beam-to-Column Connections using AVOA

Ziyu Wang^{1*}, Zhaoyang Ren²

¹Ph.D student, School of Civil Engineering, University of Birmingham, Birmingham B15 2TT, United Kingdom

²Master student, Faculty of Information Science and Engineering, Ocean University of China, Qingdao 266000, China

*Corresponding author: Ziyu Wang, zwx264@student.bham.ac.uk

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Abstract: The joint-bolt-African Vulture optimization algorithm (AVOA) model is proposed for the design of building connections to improve the stability of steel beam-to-column connections. For this algorithm, the type of steel is first determined, and the number of bolts needed by the corresponding steel type is referenced in Eurocode 3. Then, the bearing capacity of the joint can be calculated. The joint-bolt-AVOA model is established by substituting the bolt number required by the steel into the algorithm to obtain the optimal bolt number required while ensuring joint stability. The results show that the number of bolts required by the joint-bolt-AVOA model based on the stability of steel is lower than that calculated by Eurocode 3. Therefore, AVOA can effectively optimize the number of bolts needed in building connections and save resources.

Keywords: Steel connections; African vulture optimization algorithm; Optimization of bolts

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1. Introduction

In response to the current environmental issues, some researchers are using the African Vulture Optimization Algorithm (AVOA) to optimize methodology to save energy and reduce cost ^[1]. Although many animal algorithms are used in engineering problems, most are limited to solving specific mathematical problems such as cost. In recent years, researchers found that using algorithms from nature could solve and simplify several problems ^[2,3]. In addition, researchers have explored many algorithms such as the artificial bee colony, bat algorithm, and firefly algorithm to accurately solve engineering problems via a mathematical approach ^[4-7]. Therefore, using algorithms of nature to solve problems is feasible. These algorithms may have limitations when calculating the optimal solutions, but they can be used as a reference ^[8,9].

2. Methodology be based on African vultures

2.1. African vultures

Vultures are widely distributed throughout the world in America, Asia, and Europe except Australia. Most

vultures are bald, meaning they have few feathers on their heads and that is how they get their name ^[10,11]. However, it is precisely because vultures have few feathers on their heads that they usually bury their heads under their wings to keep warm during cold weather ^[12-14]. Therefore, this paper chooses African vultures as the subject to investigate the hunger rate of vultures because the climate of Africa is rarely cold, so vultures do not need to keep warm to reduce predation. Although there are wild animals in Africa for vultures to prey on, African vultures still have to fly for long periods of time in search of food due to the harsh African climate and other large carnivores ^[15,16]. Thus, these factors should be considered when investigating the vulture hunger rate ^[17,18].

Based on the above, the vulture algorithm is an algorithm that simulates the living habits and population of vultures. The algorithm is divided into four steps ^[19,20].

2.2. Stage 1 - Determine the optimal vultures within the group

After the initial vulture population is formed, the fitness of all vultures is calculated. The fittest vulture is added to the first group while the second fittest vulture is added to the second group, and the other remaining vultures are divided into first and second groups using **Equation 1**. This is recalculated in every repetition of the test.

$$R(i) = \begin{cases} BestVulture_1, & \text{if } p_i = L1 \\ BestVulture_2, & \text{if } p_i = L2 \end{cases} \quad (1)$$

In **Equation 1**, the probability of other vultures moving to the optimal grouping is calculated, where L1 and L2 are the parameters given before the search operation, whose values are between 0 and 1, and the sum of the two parameters is 1. The probability of the vultures choosing the best grouping is calculated using the roulette wheel in **Equation 2**.

$$P_i = \frac{F_i}{\sum_{i=1}^n F_i} \quad (2)$$

2.3. Stage 2 - The rate of starvation of vultures

Vultures often look for food when have high energy and feel full, which allows them to travel longer distances to find food. But if the vultures are hungry and do not have enough energy to fly for long periods of time, they would instead become aggressive and look for food near the stronger vultures. Based on this, **Equations 3 and 4** are used for mathematical modeling.

$$t = h \left(\sin^w \left(\frac{\pi \text{Iteration}_i}{2 \times \text{maxiterations}} \right) \right) + \cos \left(\frac{\pi \text{Iteration}_i}{2 \times \text{maxiterations}} - 1 \right) \quad (3)$$

$$F = (2 \times \text{rand}_1 + 1) \times Z \left(\frac{\text{Iteration}_i}{\text{maxiterations}} \right) + t \quad (4)$$

For **Equations 3 and 4**, F means when the vulture is full, iteration represents the number of current iterations, maxiterations represents the maximum number of iterations, Z is a random number that varies with each iteration through -1, h is a random number between -2 and 2, rand₁ is a random number between 0 and 1. When the Z value drops below 0, it means the vulture is hungry, and if the Z value increases to 0, it means the vulture is full. The total number of African vultures was declining, and the decline was greater with each repetition. When the value of F is more than 1, AVOA enters the exploration stage and the vultures look for food in different areas. If the value of F is less than 1, AVOA enters the development phase, and the vultures look for food near the fittest vulture. The algorithm for the vulture exploration stage is based on **Equations 5 and 6**.

$$P(i+1) = \begin{cases} R(i) - D(i) \times F, & \text{if } P_1 \geq \text{rand}_{p1} \\ R(i) - F + \text{rand}_2 \times ((\text{ub} - \text{lb}) \times \text{rand}_3 + \text{lb}), & \text{else} \end{cases} \quad (5)$$

$$D(i) = |X \times R(i) - P(i)| \quad (6)$$

For **Equations 5 and 6**, rand_{p1} is a random number between 0 and 1. P_1 is the preset exploration parameter that is used to control the exploration strategy. $P(i+1)$ is the vulture position vector in the next iteration, F is the vulture satiety rate obtained by using **Formula 4** in the current iteration, and $R(i)$ is one of the fittest vultures, rand_2 and rand_3 are random numbers between 0 and 1, ub and lb are the upper and lower boundaries of optimization respectively.

2.4. Stage 3 - Exploration

When the value F_1 is between 0.5 and 1, AVOA enters the first stage of development. Two different spin flight and siege strategies are performed in the first phase. Strategies are chosen according to P_2 as calculated in **Equation 7**.

$$P(i+1) = \begin{cases} \begin{cases} D(i) \times (F + \text{rand}_4) - d(t) \\ d(t) = R(i) - P(i) \end{cases}, & \text{if } P_2 \geq \text{rand}_{p2} \\ \begin{cases} S_1 = R(i) \times \left(\frac{\text{rand}_5 \times P_1}{2\pi}\right) \times \cos(P(i)) \\ S_2 = R(i) \times \left(\frac{\text{rand}_5 \times P_1}{2\pi}\right) \times \sin(P(i)) \\ R(i) - (S_1 + S_2) \end{cases}, & \text{else} \end{cases} \quad (7)$$

For **Equation 7**, rand_{p2} , rand_4 and rand_5 are random numbers between 0 and 1. F is the satiety rate of vultures obtained by using **Equation 4** in the current iteration, and $R(i)$ is one of the fittest vultures.

If the F value is less than 0.5, this development stage of the algorithm shown in **Equation 8** is executed. The stage involves the two fittest vultures gathering other vultures to have an aggressive struggle for the food source, with different strategies selected based on .

$$P(i+1) = \begin{cases} \begin{cases} A_1 = \text{BestVulture}_1(i) - \frac{\frac{A1+A2}{2} \times \text{BestVulture}_1(i) \times P(i)}{\text{BestVulture}_1(i) - P(i)^2} * F, & \text{if } P_3 \geq \text{rand}_{p3} \\ A_2 = \text{BestVulture}_2(i) - \frac{\text{BestVulture}_2(i) \times P(i)}{\text{BestVulture}_2(i) - P(i)^2} \times F \\ \begin{cases} R(i) - |d(t)| \times F \times \text{Levy}(d) \\ d(t) = |X \times R(i) - P(i)| \end{cases}, & \text{else} \end{cases} \end{cases} \quad (8)$$

For **Equation 8**, $\text{BestVulture}_1(i)$ is the best vulture of the first group in the current iteration, $\text{BestVulture}_2(i)$ is the best vulture of the second group in the current iteration, F is the satiety rate of the vulture calculated using **Formula 4**, $P(i)$ is the current position vector of the vulture, $d(t)$ indicates the distance between the specific vulture and the best vulture of the two groups.

3. Results of the AVOA algorithm

3.1. Results of iteration and fitness

Combined with the selection of the fittest vulture in the first step of the AVOA algorithm, this method of

selecting the optimal vulture is substituted into the design of the beam-to-column connection with the set of data from the code of F1 as shown in **Figure 1**. The figure shows that fitness and iteration are quadratic functions, and the minimum value is 0, meaning that this algorithm is relatively accurate.

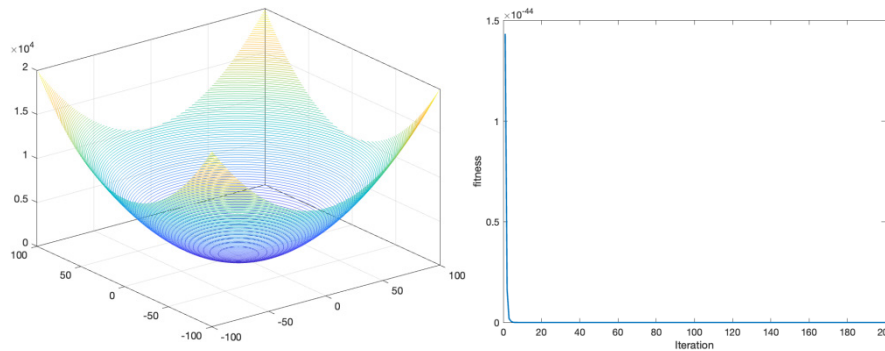


Figure 1. Qualitative results of F1 function

Figure 1 shows the graph produced by MATLAB when the number of bolts is set to 7 and the number of iterations is 200. It can be seen from the graph that when the number of iterations is 101, fitness is 0, meaning fitness is randomly generated for the roulette test, based on the equations mentioned. When the vulture keeps cycling and hunting, iterations increase while the fitness decreases. **Figure 2** shows the graph produced by MATLAB when the number of bolts is set to 8 and the number of iterations is 200. It can be seen from the graph that fitness is 0 when the number of iterations is 90.

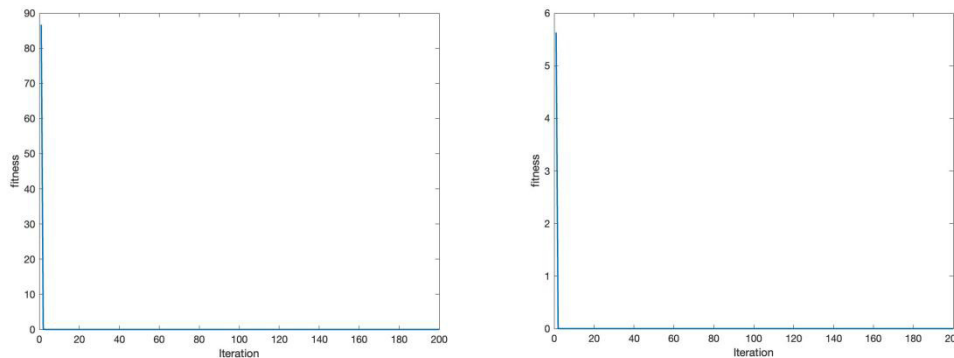


Figure 2. Iterations and fitness results of 7 bolts (left) and 8 bolts (right)

Figure 2 shows the relationship between iteration number and fitness. It can be seen from **Figure 2 (left)** that when iteration is 200 times, the maximum fitness is close to 90. As shown in **Figure 2 (right)**, when the number of iterations is 200, the maximum fitness is closer to 6. By contrast, fitness will be more accurate when the number of bolts is 7. This means that the calculations in Eurocode 3, while widely accepted, are still not precise in terms of data processing. AVOA determined a more accurate number of bolts needed in steel connections design under certain stability, thus contributing to sustainable development by reducing the bolts needed.

3.2. Discussion of AVOA

Based on data analysis, although AVOA has the advantage of high accuracy, it is still limited in terms of calculation. This is because the design proposed in this paper is only for CHS connection, whereby the bolt

specifications used are fixed, so the data analyzed by AVOA is random. When the steel class changes, the data calculated by AVOA may differ greatly from the results calculated in Eurocode 3, resulting in a lower number of bolts estimated. Therefore, the study based on AVOA needs to be further researched for future reference.

4. Conclusion

In this paper, steel beam-to-column connections are designed using the African vulture algorithm to find the optimal solution to the multidimensional optimization problem by referring to the flight and predation behavior of the African vulture. AVOA algorithm can effectively deal with multidimensional optimization problems with fast convergence speed and has a good global search ability. However, this algorithm is sensitive to the selection of the initial population and requires appropriate parameter setting and adjustment. Therefore, different quantities of bolts are studied in this paper. By comparing the calculation steps and standard quantities in Eurocode 3, it is concluded that the AVOA algorithm is relatively accurate, which means that 7 bolts can stabilize the structure while ensuring the stability of the connection. However, Eurocode 3 requires 8 bolts for the same steel and bolt class to maintain the stability of the structure. Hence, the AVOA calculation has shown that one less bolt is required for each connection during construction, thus reducing the overall number of bolts required for the whole building, which is in line with sustainable development. However, AVOA calculations were only performed on CHS steel and class 8.8M24 bolts with 26 mm diameter clearance holes in this paper. Therefore, the results obtained are limited and inconsistent. However, this paper has at least achieved the result of optimizing the number of bolts for the connections of this design. This finding can be a reference for the future design of AVOA and steel beam-to-column connections.

Disclosure statement

The authors declare no conflict of interest.

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