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Self-Adaptive Genetic Algorithm For Bucket Wheel Reclaimer Real-Parameter Optimization

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ABSTRACT Bucket wheel reclaimer (BWR) is a complex engineering machine widely used in the open pit mine; it is characterized by the low efficiency and high maintenance cost. The boom, namely a typical framework structure, is a core component of BWR, which affects the performance of the BWR directly. For addressing this issue, this paper proposes a self-adaptive genetic algorithm (AGA) to improve the performance of the genetic algorithm (GA). The standard genetic algorithm has been improved to enhance the optimization efficiency, because the optimization problem is believed to be highly non-linear. The AGA has been verified by two framework structures, and the results of AGA are compared with the corresponding results of previous literature. Furthermore, the AGA is applied to obtain the optimal size and shape of the BWR boom by taking the BWR boom as a space framework structure, and improve BWR's performance by meeting the requirements of the intensity and rigidity. The results show that the improved genetic algorithm has a higher efficiency than the standard GA. The structure optimization of the BWR boom is performed using the AGA. From the optimization, BWR boom's weight decreases by 23.46% from the initial weight.

INDEX TERMS Bucket wheel reclaimer, framework structure, improved genetic algorithm, structural shape optimization.

I. INTRODUCTION

Bucket wheel reclaimer (BWR) is one of the most widely used transmission mechanisms in the open pit mine. From the viewpoint of design, the components of the BWR should be designed to have sufficient strength, or unpredictable accidents may happen [1]. Although the conventional design does not take the lightweight design into account and can avoid accidents, the consequences of such design are the waste of materials in manufacture and the waste of energy during work. In structural engineering, the optimization aims mainly at designing structures with high efficiency, while their design and construction require minimum cost and materials [2]. The BWR boom occupies almost 50% percent of the whole weight of the actuator, so an inappropriate structure design may lead to large material waste and economic cost. As seen, it is essential to perform the lightweight design for the BWR.

BWR boom is a typical framework structure. Various techniques based on classical optimization methods have been developed to find optimal truss structures [2]–[4]. Most of these techniques can be classified into three categories, including sizing, configuration, and topology optimization. Goldberg and Samtani [6] used only size optimization, as well as Rajeev [7]. Hejela et al. [8] obtained the optimal topologies and optimal member areas for each of the truss topologies. Rajan [9] optimized two 2-D truss topologies with three methods, and taken the member areas and change in nodal displacements as variables. Song et al. [10] proposed an advanced hybrid surrogate model, which can be optimized accurately for engineering optimization problems. Kaveh and Javadi [11] utilized particle swarm optimization algorithm (PSO) to optimize the truss with multiple natural frequency constraints. Gomes [12] used the particle swarm optimization (PSO) algorithm to optimize the truss structures with frequency constraints.

According to ''No Free Lunch'' theorem, the global optimal solutions for all optimization problems can't be solved with a single meta-heuristic algorithm. For addressing this issue, to perform the global optimization of the BWR boom, an adaptive genetic algorithm (AGA) has been proposed in this study. The AGA algorithm converges faster than the standard genetic algorithm and has a low computational cost.

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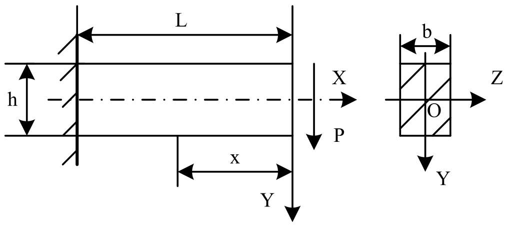

FIGURE 1. **The model of cantilever beam.**

The remainder of the paper is organized as follows. Section 2 develops a statement of the optimization problem. The adaptive genetic algorithm (AGA) framework is established in Section 3, including the physical background of the genetic algorithm and the flowchart of AGA. Section 4 verifies the AGA algorithm. The optimization of BWR boom is dealt with in section 5. Section 6 gives the concluding remarks.

II. STATEMENT OF THE OPTIMIZATION PROBLEM

In general, the primary objective of structural optimization problems is to find a design that minimizes the structural weight or cost while satisfying strength and serviceability constraints [13]. In this paper, the purpose is to obtain the optimal size and shape of the framework for structural weight under stress constraints. The optimization model with stress constraint can be given by:

$$\begin{cases} find \ \{\boldsymbol{x}\} = [x_1, x_2, \cdots x_n] \\ \min \ f(\{\boldsymbol{x}\}) = \sum_{i=1}^{n} \rho \cdot A_i \cdot l_i \quad (i = 1, 2, \cdots, n) \\ s.t. \ \ 0 < s \cdot \sigma_i < [\sigma]_i \\ \quad\quad x_{i\min} < x_i < x_{i\max} \quad i = 1, 2, \cdots, n \end{cases} \tag{1}$$

where $\boldsymbol{x}$ is the design variables; f denotes the mass of the system; n presents the number of design variables; ρ is the material density; A_i is the cross-sectional area of the beam of ith member; l_i is the length of the beam of ith member; s is the safety factor; σ_i and $[\sigma]_i$ denote the strength and yield strength of ith member, respectively; $x_{i\min}$ and $x_{i\max}$ present the lower and upper bounds of the design variable x_i, respectively.

To simplify the constraints, a simple method to determine the stress function is employed. According to the characteristics of the cantilever beam, the model of a cantilever beam is shown in Fig. 1.

In the Fig. 1, h, b and L are the length, width and height of the cantilever beam, respectively; P is the load; x is the distance from the load. In the process of solving the cantilever beam problem, stress function is necessary to be confirmed. The stress function is given by:

$$\nabla^4 \phi = 0 \tag{2}$$

where ϕ presents stress function.

For a long rectangular beam, the stress component can be expressed as:

$$\begin{cases} \sigma_x = M(x) f(y) = \frac{\partial^2 \phi}{\partial y^2} \\ \sigma_y = q(x) f(y) = \frac{\partial^2 \phi}{\partial x^2} \\ \tau_{xy} = Q(x) f(y) = \frac{\partial^2 \phi}{\partial x \partial y} \end{cases} \tag{3}$$

where $q(x)$ is the is distributed load on the beam; Q (x) denotes the shear force on the beam cross-sectional area; and M (x) is the bending moment on the beam cross-sectional area. Based on the above assumptions, this paper assumes σ_x can be expressed as:

$$\sigma_x = M(x) f(y) = (Px) \cdot y \tag{4}$$

By substituting the integral Eq.(4) into Eq.(3), then integral to y, the relationship between f_1, f_2 and ϕ can be obtained.

$$\phi = \frac{1}{6} Axy^3 + f_1(x)\, y + f_2(x) \tag{5}$$

where A is the constant associated with the initial value of the integral; $f_1(x)$ and $f_2(x)$ are intermediate variables generated during the integration process, respectively. By substituting stress function Eq. (5) into biharmonic Eq. (2), which is obtained from the elastic mechanics, then the Eq.(6) can be given by:

$$y \frac{d^4 f_1(x)}{dx^4} + \frac{d^4 f_2(x)}{dx^4} = 0 \tag{6}$$

According to Eq. (6), the following equation can be obtained:

$$\frac{d^4 f_1(x)}{dx^4} = 0 \tag{7}$$

$$\frac{d^4 f_2(x)}{dx^4} = 0 \tag{8}$$

By combining Eqs. (5) and (6), the stress function is obtained:

$$\phi = \frac{P}{6} xy^3 + y\left(Bx^3 + Cx^2 + Dx\right) + \left(Fx^3 + Gx^2\right) \tag{9}$$

where B, C, D, F and G are the constants associated with the initial values of the integral, respectively.

III. ADAPTIVE GENETIC ALGORITHM (AGA)

A. THE PHYSICAL BACKGROUND OF GENETIC ALGORITHM (GA)

Proposed by Holland [14] in the early 70s, the GA is a very popular meta-heuristic search algorithm that iteratively updates a set of chromosomes (called a population) representing solutions, each with an associated fitness value, using the Darwinian principle of natural selection and using genetic operations, such as crossover and mutation [15], [16]. Up to now, GA has drawn much attention, because it can handle the complex and unstructured optimization problems and doesn't require initial values. Although GA has many advantages, it has some shortcomings, e.g., the slow speed convergence, even non-convergence. In order to improve the convergence speed and reduce computational costs, this paper proposes an adaptive genetic algorithm (AGA) to overcome the shortcomings mentioned above.

The crossover and mutation probabilities are the key factors that affect GA's behavior and performance. The greater the crossover probability is, the faster the new individuals will be produced. If the crossover probability is too large, the genetic model can be destroyed, and the individuals' structure with high fitness can be destroyed as well, which will slow GA's search process. On the contrary, the smaller the crossover probability is, the less likely the new individuals are generated. In this situation, GA is the same as the random search algorithm.

B. PROCEDURE OF AGA

To overcome the above-mentioned deficiencies, an adaptive crossover rate (p_c) and mutation rate (p_m) is enhanced in the AGA. The improved algorithm can make the crossover and mutation rate automatically change with the fitness. When the individual's fitness is the same or the local optimal value is obtained, the crossover and mutation rates will increase; otherwise, the crossover and mutation rates will decrease. When the fitness value is higher than the individual's average, it corresponds to a lower probability of crossover and mutation, so that the individual is protected. On the contrary, the individual is eliminated.

The mutation rate is one of the important factors in GA. The function of mutation is to prevent GA from obtaining sub-optimal solutions, which result from a premature convergence in the populations. In the standard GA, however, the mutation rate is performed by a constant. To obtain the adaptive mutation rate, this study uses the method developed by Srinivas and Patnaik to obtain the adaptive mutation rate. The adaptive mutation rate can be expressed as:

$$P_c = \begin{cases} \dfrac{k_1\left(f_{\max} - f\right)}{f_{\max} - f_{avg}}, & f \geq f_{avg} \\ k_2, & f < f_{avg} \end{cases} \tag{10}$$

where $f_{\max}$ is maximum fitness value of individuals in population; f_{avg} denotes the average fitness value of individuals in population; f is the larger one among the two individual fitness values to cross; and k_i $(i = 1, 2)$ is a constant, the region of which is (0,1).

There are many crossover methods for the AGA, including one point, two points, more points and uniform crossover. The function of crossover is to obtain a new chromosome, which can keep a high fitness. Increment of the individual fitness can decrease the crossover rate, that is, an individual with high fitness will emerge in the next population. In this paper, the cross operation uses a single point crossover operator, and the adaptive crossover is operated as presented in Eq. (9):

$$P_m = \begin{cases} \dfrac{k_3\left(f_{\max} - f'\right)}{f_{\max} - f_{avg}}, & f' \geq f_{avg} \\ k_4, & f' < f_{avg} \end{cases} \tag{11}$$

where, f' is fitness value of the individual variation and k_i $(i = 3, 4)$ is a constant, the region of which is (0,1).

AGA is an improved genetic algorithm by obtaining the greatest fitness of the individual in the next population, which can be considered as an elitist strategy. The foremost reason is that the crossover and mutation probabilities of each optimization problem are not the same. Therefore, the adaptive crossover and the adaptive mutation operators have been performed in this study. The flowchart of the AGA is shown in Fig. 2.

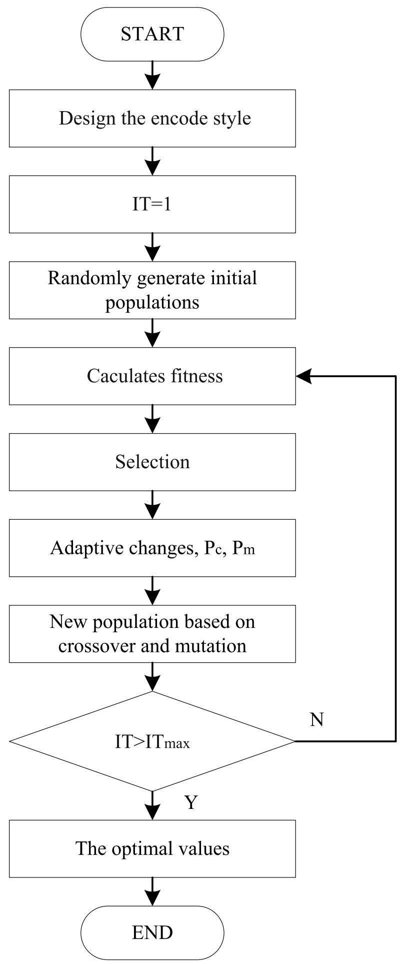

FIGURE 2. **The flowchart of AGA.**

IV. NUMERICAL EXPERIMENT

This paper selected two kinds of plane frameworks to verify the superiority of the AGA, including size optimization of a 10-bar cantilever frame with 10 design variables, and size optimization of an 18-bar cantilever framework with 4 design variables.

A. THE10-BAR PLANE FRAMEWORK

The 10-bar plane framework is a well-known benchmark problem [17], as illustrated in Fig. 3. The material of all the members of the framework are aluminum with the elastic modulus being 6.90×10^{11} Pa, and the mass density being 2800 kg/m^3. The cross-sectional areas of all members are

TABLE 1. Deformation of the results for the 12-bar framework.

Variables No.	Design name	Areas (mm^2) Renwei and Peng [18]	Li et al. [19]	Perez and Behdinan [20]	Mustafa Sonmez [21]	Present work
1	A1	19735.44	19806.41	21612.86	21645.12	19722.54
2	A2	64.52	64.52	64.52	64.52	64.52
3	A3	15012.87	14954.81	14690.29	14954.81	14974.16
4	A4	9799.98	9793.53	9303.21	9819.34	9799.98
5	A5	64.52	64.52	64.52	64.52	64.52
6	A6	296.77	355.48	64.52	354.84	361.29
7	A7	4838.70	4812.89	4864.51	4812.89	4851.60
8	A8	13593.52	13535.46	13206.43	13587.07	13529.01
9	A9	13858.04	13877.40	13154.81	13870.94	13838.68
10	A10	64.52	64.52	64.52	64.52	64.52
Constraint violation		None	None	23.95×10^{-3}	None	None

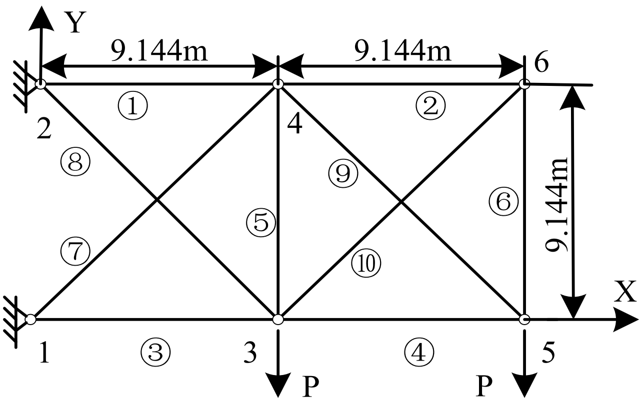

FIGURE 3. Configuration of the 10-bar plane framework.

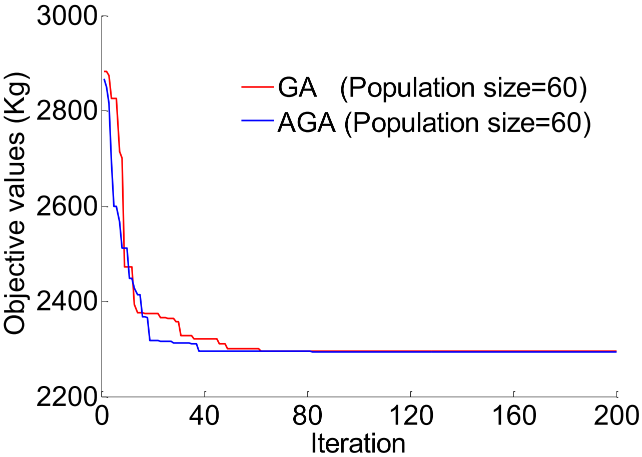

FIGURE 4. The convergence history of the 10-bar plane framework.

the same. The cross-sectional areas of all members are variables. The maximum and minimum cross-sectional areas are 64.516 mm^2 and 22580.6 mm^2. Apply 666.2 kN on point 3 and 5, the direction of the force is along the negative direction of Y axis.

From Fig. 4, it can be known that the iterations of AGA is less than that of the standard GA, and the optimal values can be obtained with the AGA with less number of iterations. Although the convergence speed of the two algorithms are not the same, the optimal values of the two methods are very similar. To verify the accuracy of the AGA, this paper compares the results with some previous works. All the previous works used different optimization approaches including the optimality criteria [18], the heuristic practical swarm optimization (HPSO) algorithm [19], and the particle swarm optimization (PSO) algorithm [20] to perform the same optimization as listed in Table 1. It is interesting to note that the results of the present work are similar to those of previous scholars.

B. THE18-BAR PLANE FRAMEWORK

This paper selects the 18-bar plane framework, which is another standard plane framework case, to verify the correctness of AGA. The configuration of the 18-bar plane framework is shown in Fig. 5. The material of the framework is again set to be aluminum with the elastic modulus being 6.90×10^{10} Pa, and the mass density being 2800 kg/m^3. The cross-sectional areas of all members are variables. The maximum and minimum cross-sectional areas are 64.516 mm2 and 32258 mm2, respectively. The force of the plane framework is shown in Fig. 5. The concentrated force is $P = 88.96\ kN$, the direction of the force is along the negative direction of Y axis.

Fig. 6 shows similar results to Fig. 4, which is the iterations of the AGA is less than that of the traditional GA. This standard plane framework case is also compared with the previous literatures' results. The optimal values from 4 independent runs of the AGA are presented in Table 2. In addition, this table contains other published results of the same problem using different optimization methods, including the multiplier method [22] and the HS algorithm [23]. By comparison with the data in the Table 2, it is interesting to note that the maximum of the deviation is less than 1%.

V. STRUCTURE OPTIMIZATION OF THE BWR BOOM

A. STRUCTURAL COMPONENTS OF THE BWR

The BWR is a major complex equipment widely used in construction, mining, etc. due to its advantages, such as operation

TABLE 2. Deformation of the results for 12-bar framework.

Variables No.	Design name	Areas (mm^2) Imai and Schmit [22]	Lee and Geem [23]	Present work
1	A_i (i=1,4,8,12,16)	6451.6	6451.6	6451.6
2	Ai i=2,6,10,14,18)	13967.71	13967.71	13954.81
3	A_i (i=3,7,11,15)	8064.5	8058.05	8077.40
4	A_i (i=5,9,13,17)	4561.28	4554.83	4561.28
Constraint violation		0.26×10^{-3}	7.51×10^{-3}	0.36×10^{-3}

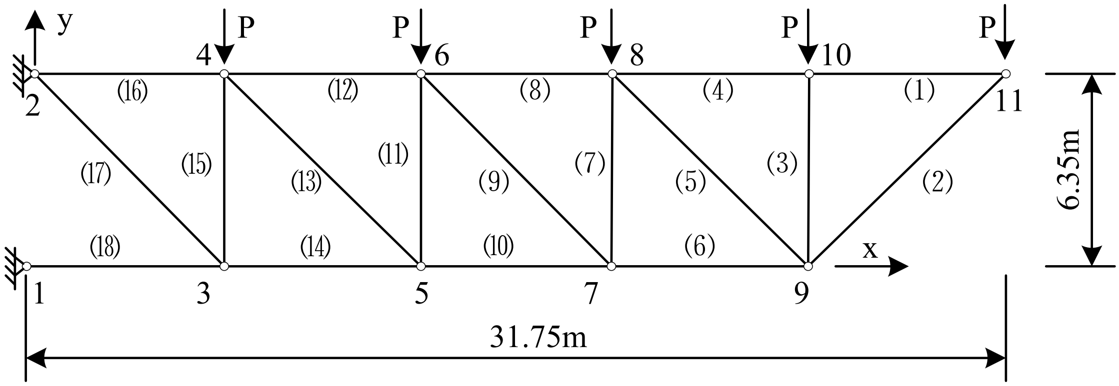

FIGURE 5. Configuration of the 18-bar plane framework.

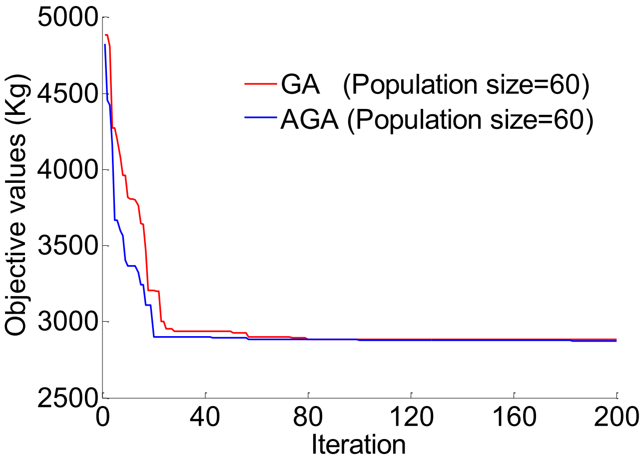

FIGURE 6. The convergence history of the 18-bar plane framework.

simplicity and high efficiency. As illustrated in Fig. 7, the BWR consists of three major components, including the upper body, the lower body and the attachment.

As the basis of entire BWR, the lower body provides a stable base for the machine and includes the proper drive and crawler system. The upper body serves as a platform for the machinery and it is a core part of the BWR to realize the valid operations, such as the digging, the lifting, and the revolving. The attachment is the implementing agencies of the BWR, including boom, bucket-wheel and guy rope.

B. OPTIMIZATION OF BWR BOOM

As mentioned in previous section of this paper, lightweight for BWR boom is essential, because the components consume much energy including the materials, electrical energy, etc. To reduce the power of the BWR boom consumed, this paper studies lightweight of BWR boom, namely the optimization of shapes and sizes, by taking into account the stress constraints.

The material of the space framework is set to be the steel with the elastic modulus being 2.1×10^{11} Pa, the Poisson ratio being 0.3, and the mass density being 7860 kg/m3. The cross-sectional areas of all members are classified into four main categories, which are shown in the Fig. 8. The concentrated force is $P = 34.81$ kN on the three front-end nodes and adds the gravity to all member. The structure of the BWR boom has many parameters because it is complicated. To obtain the global optimal values for the optimization problem, this paper chooses the proposed AGA to solve the optimization problem. Configuration of the BWR boom is shown in Fig. 8.

The signs of "+" and "−" denote the improvement of the optimal objective values compared with the initial value. It should be noted that "+" denotes increase and "−" denotes decrease. As can be seen from Fig. 9, when the iteration reaches at the 114th iteration, the objective function tends to be stable. The objective value decreases from 1.07×10^5 Kg

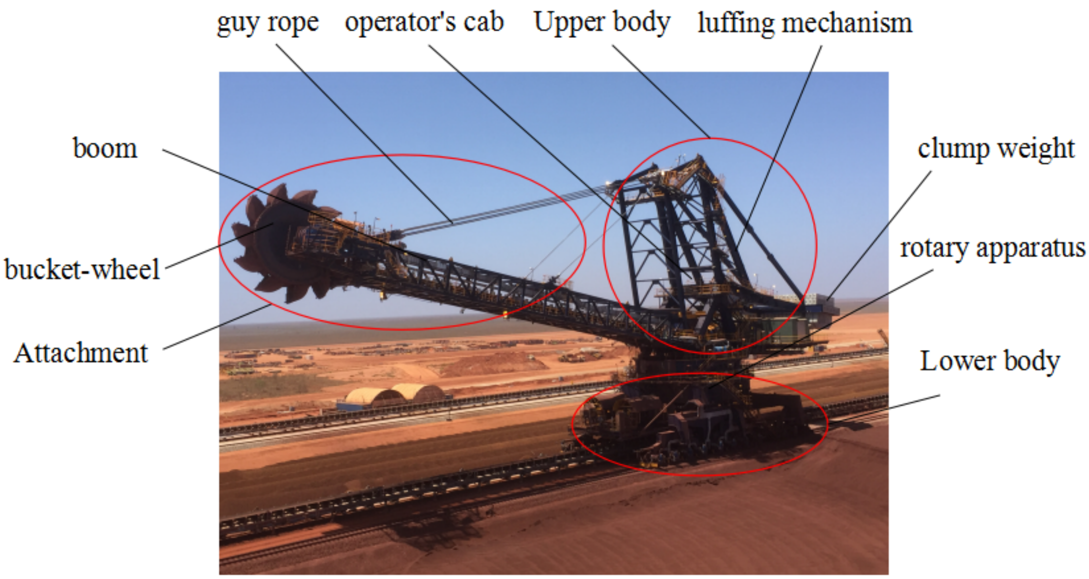

FIGURE 7. The BWR' structure.

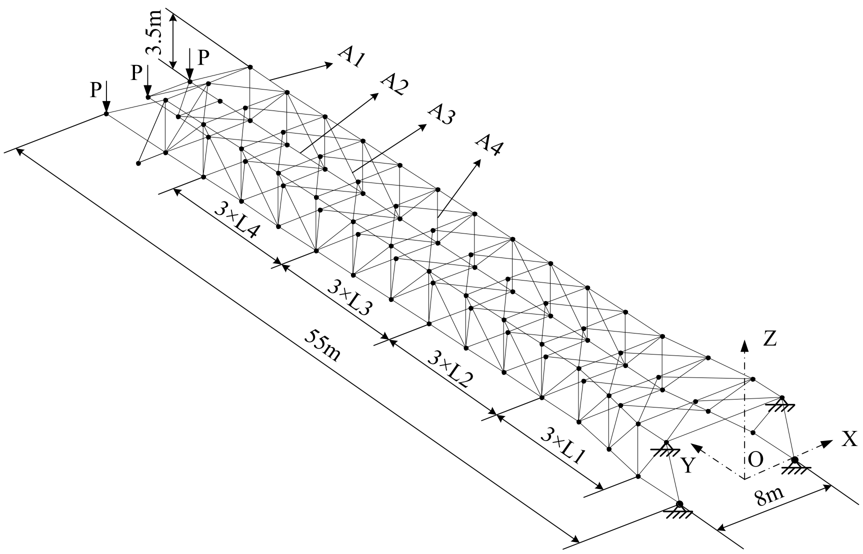

FIGURE 8. Configuration of the BWR boom.

TABLE 3. Optimization results for the BWR boom.

Design variable	Initial value	Optimal value	Improved
L1	3.50 m	4.48 m	+27.93%
L2	3.50 m	3.75 m	+7.16%
L3	3.50 m	3.47 m	-0.91%
L4	3.50 m	2.12 m	-39.43%
A1	1.10E-2 m^2	1.20E-2 m^2	+11.54%
A2	2.30E-2 m^2	1.60E-2 m^2	-31.64%
A3	7.00E-3 m^2	4.00E-3 m^2	-32.89%
A4	1.00E-2 m^2	9.00E-3 m^2	-8.93%

to 8.19×10^4 Kg. Table 3 reports the optimization results of these design variables of the BWR boom. The optimized L4 decreases by 39.14% from 3.50 m to the optimized 2.12 m. By comparing with the data in the Table 3, it is interesting to note that the results of the AGA can reduce weight greatly.

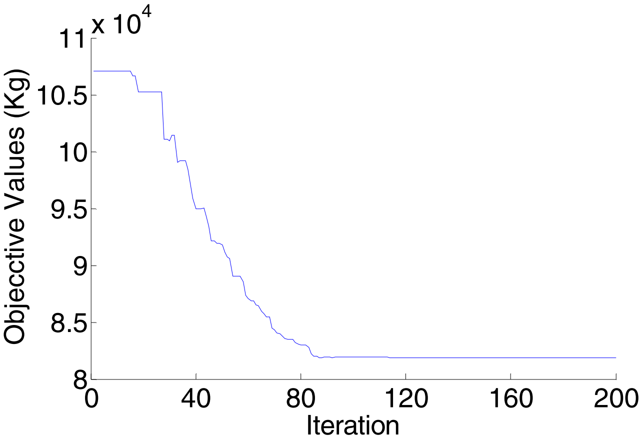

FIGURE 9. Typical convergence history of the BWR boom.

VI. CONCLUSION

Structural optimization with stress constraints is a challenging study, which is characterized by non-convex and highly nonlinear optimization problems. In this paper, the AGA has been proposed to optimize the BWR boom. The accuracy of AGA have been verified by two frameworks structures. The results illustrate the convergence speed and calculation cost of the AGA are smaller than the traditional GA. Moreover, the results are similar to the literatures results above 97%. The numerical results of the examples bring out the advantages of the AGA method in terms of speed of convergence and optimality of the final solutions.

To obtain the global optimal values of the BWR boom, the shape and size space framework optimization problems with stress constraints are considered. BWR boom has many variables, including four length parameters and four cross-section parameters. The optimization problems are solved by the framework code and AGA, which have been verified as mentioned above. The results show that BWR boom's weight is reduced from 1.07×10^5 Kg to 8.19×10^4 Kg. The optimization of the BWR boom is given as an example, which demonstrates that the AGA are helpful to the framework structure optimization.

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