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Optimal design of truss structures via an augmented genetic algorithm

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Abstract: This paper investigates the application of an augmented genetic algorithm (AGA) for the problem of optimal design of truss structures. The problem is to determine the minimum value of the weight/cost associated with the truss structure design while a set of stress and displacement constraints are to be satisfied. The proposed AGA exploits a probabilistic selection procedure based on the annealing process. Moreover, a new enhancing trick is proposed that prevents familial reproduction. This effect restrains the degenerative phenomena during the evolution of the canonical genetic algorithm (GA). Accordingly, a considerable improvement in converging speed is achieved. This advancement could be extremely advantageous in large structure design problems, where the existing methods suffer from long execution times. Various benchmark examples are examined to demonstrate the performance of the proposed method. Moreover, the obtained results are compared with those of existing methods to verify the effectiveness of AGA optimization.

Key words: Optimal design, truss structures, augmented genetic algorithm (AGA), truss optimization, familial reproduction

1. Introduction

Steel truss structures are broadly used in real-world applications and a continuing motivation for research in optimal structural design exists. This observation is mainly due to the limited material and energy resources. The configuration optimization (even topology optimization) of steel trusses can provide a remarkable reduction in the weight and cost as a direct result. The problem involves determining the joints' coordinates and members' cross-sectional areas and lengths.

Most previous optimal structure designs are based on analytical optimization methods, e.g., Lagrangian relaxation (Schmit and Fleury, 1980; Juang et al., 2003) or branch and bound technique (Sandgren, 1990), which necessitate much gradient information. Owing to the nonlinear inherent nature of structure design problems and having mixed discrete and continues variables, the analytical approaches necessitate rigorous efforts, particularly in realistic situations. Mathematical programming, particularly mixed-integer programming (MIP), has also been applied in structural design optimization (Bollapragada, 2001). Generally, the advantages of MIP over other analytic methods are as follows: 1) global optimality; 2) direct measure of the optimality of a solution; and 3) accurate modeling capabilities (Williams, 1999). The MIP solver could guarantee a solution that is globally optimal or one within an acceptable tolerance. In contrast, the key disadvantage of MIP is the necessity of

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explicit mathematical models of all problem equations with linear relations (Nemhauser and Wolsey, 1998). This is while the majority of practical problems are not intrinsically linear. In these situations, the linearization processes on one hand impose further mathematical complexities and on the other hand impose some level of errors, which might not be trivial enough. The other shortcoming of MIP is the non-polynomial relation of execution time with respect to the problem dimension and decision variables (Nemhauser and Wolsey, 1998). This attribute could be restrictive in large-scale problems.

Based on the above considerations, the application of soft-computing optimization methods has shown significant growth in recent years. Among them are genetic algorithm (GA) (Yang and Soh, 1997), particle swarm optimization (Rasouli, 2010), artificial bee colony (Hadidi, 2010), and simulated annealing (Zhang and Wang, 1993). These methods are meta-heuristic and have the following common features:

- They are mostly meta-heuristic approaches inspired by natural or biological phenomena,
- They do not necessitate an explicit mathematical modeling of the problem at hand,
- They offer an unlimited potential in coping with real-world design problems where engineering knowledge plays a vital role,
- They reveal prosperous and effective outputs in many science and engineering areas where optimization is highly desired.

Against the aforementioned superiorities, the major drawbacks are the rather expensive computational effort and probably long execution times. Thus, various research works are ongoing to further enhance meta-heuristic-based optimization methods. These modified approaches intend to accelerate the solving procedure by preventing ineffective events. Moreover, combined methods are proposed as well in which the capabilities of different methods are concurrently utilized to offer a more advantageous technique.

In this paper, the problem of optimal design structure is addressed by proposing a new augmented genetic algorithm (AGA) method. The proposed AGA method is an enhanced version of GA where a new selection method based on the annealing procedure is utilized. This modification improves the exploitation aspect of the GA. Furthermore, a new effect referred to as familial reproduction avoidance is utilized. This effect prevents the degenerative phenomenon and ultimately promotes the optimization process efficiency. Numerical evidence by analyzing benchmark examples is provided and compared with that of other existing methods.

The rest of the paper is organized as follows. Section 2 briefly defines the optimal structural design of the truss. Section 3 introduces the proposed optimization methodology. In Section 4, numerical achievements and their comparison with those of existing methods are presented. Section 5 concludes the paper.

2. Optimization of truss structures

The configuration optimization design of trusses can be mathematically expressed by

$$minimize \;\; w(A,x) = \sum_{i=1}^{m} \rho A_i L_i = \sum_{i=1}^{m} \rho A_i \sqrt{\sum_{j=1}^{3} (x_{ij}^{a} - x_{ij}^{b})^2} \tag{1}$$

subject to

$$g_k(A,x) \le 0; \qquad k = 1, \ldots, p \tag{2}$$

and

$$\underline{x} \le x \le \overline{x} \tag{3}$$

where w is the total weight of the structure as a function of problem decision variables, A and x.

Vector $A = [A_1, A_2, \ldots, A_m]^T$ denotes the cross-sectional area of members to be adopted among a list of discrete variables.

Matrix x represents the elements coordination in 3 dimensions and is defined as

$$x = \begin{bmatrix} x_{11}^a & x_{12}^a & x_{13}^a & x_{11}^b & x_{12}^b & x_{13}^b \\ x_{21}^a & x_{22}^a & x_{23}^a & x_{21}^b & x_{22}^b & x_{13}^b \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{m1}^a & x_{m2}^a & x_{m3}^a & x_{m1}^b & x_{m2}^b & x_{m3}^b \end{bmatrix} \tag{4}$$

where subscripts a and b stand for both ends of each member. These decision variables are inherently continuous and should be dealt with as they are or discretized based on small enough intervals.

In Eq. (1), ρ is the material density and is assumed to be identical for all elements. Otherwise ρ_i should be used in the formulation. A_i and L_i are the cross-sectional area and length of the i^{th} member, respectively.

The problem inequality constraints are expressed in Eq. (2). These constraints are usually defined in design codes and commonly include stress, displacement, and buckling constraints. A feasible solution should satisfy all the constraints and great care is needed in this regard. The coordination of a given member at each dimension might be limited to upper and lower bounds. The matrix representation of these limits is shown in Eq. (3).

Similar to other meta-heuristic algorithms, the problem constraints are handled via the penalty function approach. Accordingly, the summation of constraints' violations is multiplied with a considerably large penalty coefficient and the result is added to the objective function. Since the penalty term is very dominant compared to the structure weight, feasible solutions definitely meet the problem constraints.

The mathematical model defined above has nonlinear relations of the objective function and constraints with respect to the decision variables. Thus, this is a nonlinear constrained optimization problem with mixed discrete and continuous variables.

3. The proposed optimization algorithm

Among the outstanding algorithms that have surfaced in recent decades are the GA (1975), simulated annealing (1983), particle swarm optimization (2002), ant colony optimization (1997), and evolutionary algorithms (1995) (Haupt and Haupt, 2004). These algorithms represent natural processes that are remarkably successful at optimizing natural phenomena. They rely on an intelligent search of a large but finite solution space using statistical methods. The algorithms do not require taking cost function derivatives and can thus deal with discrete variables and noncontinuous objective functions. However, mathematical tricks such as discretization of continuous variables into discrete ones more generalize the application of meta-heuristic algorithms.

In the following, the essential background of GA is discussed and the proposed method is thereafter introduced.

3.1. Genetic algorithm (GA)

GA was inspired by the natural evolution of species. In natural evolution, each species searches for beneficial adaptations in an ever-changing environment. As species evolve, new genetic information is encoded in the chromosomes. This information changes with the exchange of chromosomal material during breeding (crossover) and also mutation (Goldberg, 1989). From the engineering standpoint, if we have 2 solutions with good approximation for a given problem, their combination might lead to a better solution. Thus, GA pertains to the search algorithms with an iteration of generation-and-test (Jiao and Wang, 2000). With the characteristics of easier application, greater robustness, and better parallel processing than most classical methods of optimization, GA has been widely used for combinatorial optimization (Muhlenbein, 1992), structural designing (Miller et al., 1989), machine learning rule-based classifier systems (Tokinaga and Whinston, 1992), etc. The major disadvantage associated with GA is that the evolution process is usually very slow. This characteristic imposes very large execution times in practical problems with hundreds of decision variables.

3.2. Augmented genetic algorithm (AGA)

Crossover and mutation as 2 operators of GA give each individual the chance of optimization and ensure the evolutionary tendency with the selection mechanism of survival of the fittest. Since the 2 genetic operators make individuals change randomly and indirectly during the whole process, they can cause certain degeneracy. In some cases, these degenerative phenomena are very obvious, restricting the application of GA.

The immune algorithm (IA) is a new adaptive selection procedure mainly based on the annealing process (Jiao and Wang, 2000). This procedure is commonly referred to as *immune selection* and restrains or avoids repetitive and useless work during the course, so as to overcome the blindness in action of the crossover and mutation. During the actual operation, this trick avoids the degenerative phenomena arising from the evolutionary process, thus making the fitness of population increase steadily. Based on numerical evidence in IA applications, a considerable enhancement in the performance of the optimization process has been reported (Jiao and Wang, 2000).

Here, we employ immune selection as the procedure to choose the individuals, i.e. solutions, for the next generation. Accordingly, the proposed AGA method can be illustrated as in Figure 1.

In the conventional GA, the new generation is reproduced by crossover and mutation operations running over the existing parents. This approach expands the exploration feature of the search process while its exploitation facet might be sacrificed. The reason is that, if the existing parents are more eligible than the offspring set, the average fitness of the new generation would decrease, and this is not desirable from the optimization point of view. In the proposed AGA method, the immune selection process is considered to preserve the exploitation aspect while not overlooking the exploration facet as well. Immune selection consists of 2 stages. The immune test is the first one to be continued to test the new individual. If the fitness of offspring is lower than that of the parent, which shows that a serious degeneration has happened in the process of crossover or mutation, the parent will participate in the next competition instead of the individual. The second stage is the probabilistic selection based on the annealing process, which means that the probability of joining individual s_n to the new parents is as below:

$$P(s_n) = \frac{e^{f(s_n)/T_k}}{\sum\limits_{g=1}^{n_o} e^{f(s_g)/T_k}} \tag{5}$$

where n_0 is the number of present offspring, $f(s_n)$ is the fitness of the individual n, and T_K is the annealing temperature approaching zero with the progress of generations. In the probabilistic selection procedure, the range [0, 1] is divided into n_0 intervals with ranges obtained by Eq. (5). Then the selection of a new individual is fulfilled by generation of a uniform random number.

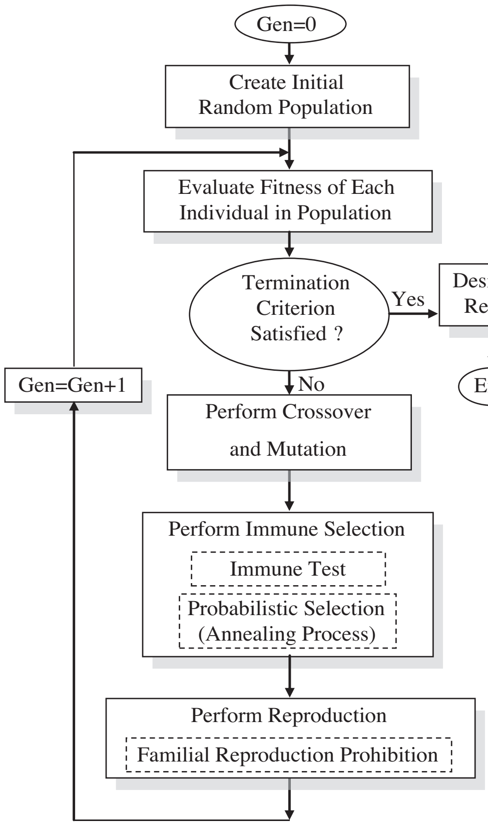

Figure 1. AGA flowchart.

The annealing temperature in Eq. (5) has an adaptive inherent and is calculated by

$$T_k = \ln(\frac{T_0}{k} + 1), \qquad T_0 = 100 \tag{6}$$

where k is the generation number.

3.3. Familial reproduction effect

Genetic investigations have proven that in the human species familial reproduction results in some disorders and diseases in the offspring (Chen, 2006). Considering that in most human societies marriage between 2 parents' offspring, i.e. a son and a daughter from identical parents, is illegal and against religious principles, this observation has been inferred from higher level familial marriages, e.g., between cousins. However, it is expected that the degenerative effect of familial recombination between offspring generated from identical parents appears similar to that of other familial marriages. We called this phenomenon the *familial reproduction effect* and try to investigate it on and by means of the considered problem. Figure 2 illustrates this phenomenon in a simple pictorial manner.

The left-hand side of Figure 2 shows the recombination of 2 parents while generating 2 offspring. Since the parents are likely to have good fitness as they are selected for mating, both offspring have the chance to be better than the parents based on the *building block schemata*. Assuming that these offspring are adopted to mate in the next generation(s), it is probable to generate their parents as depicted clearly by the right-hand side of Figure 2. However, from a generic point of view, even if the crossover point of offspring in the generation of Gen+1 is different from that of their parents, the resultant offspring have great similarities to their grandparents or maybe their aunts or uncles. Occurrence of this phenomenon results in repetitive and useless work during the solution search course and reduces the converging speed.

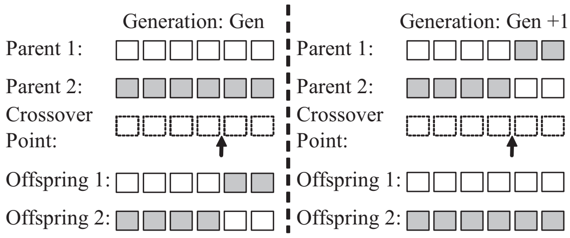

Figure 2. Familial crossover effect.

Based on the above consideration, it is expected that avoiding familial mating up to a given level can enhance the converging process of the algorithm and its efficiency. For the sake of implementation, it is assumed that each individual has a unique ID (such as: {(generation number),(individual number)}) and is tagged with the parents' IDs. When the offspring are selected for mating, their parents' IDs should be different. Otherwise, the reproduction is canceled and other parents are selected. Depending on the order of generations to be prohibited in reproduction, the offspring should carry the IDs of parents, grandparents, and upper-level ancestors. Evidently, how the familial reproduction prohibition is implemented is the same for both sorts of crossover operations, i.e. fixed or variable points.

Simulation results on the structure design optimization problem verify the expected results associated with this phenomenon, particularly when the number of individuals in each population is small. However, similar to the other ideas in the field of heuristic algorithms, this cannot be a general observation and should be examined in specific cases.

4. Numerical results

The parameters of a given optimization method are the characteristics most influencing its performance. The process of tuning these parameters is hence an underlying requirement and should be fulfilled in a perfect manner. This process is usually performed by either a trial and error procedure or a separate heuristic algorithm. In this paper, we tuned up the AGA parameters through the former method and based on 50 executions.

The characteristics of the AGA are as follows: single point crossover, mutation rate of 0.5%, 50 chromosomes for each population, and roulette wheel fitness based selection. The best result found in all generations is considered the solution of the problem. The stopping criterion of the program is adopted as observing no improvement in the last 20 successive generations.

In the following the performance of the proposed method is examined by various benchmark examples of truss design problems. In these examples, the coordinates of the truss nodes are fixed and just the elements' cross-section areas are the problem decision variables. The obtained results are also compared with those associated with some other available methods to reveal the quality of answers. The execution times associated with the obtained optimal solutions are reported as well. The technical specifications of the computer used for simulations are Core 2 Quad 2.33 GHz CPU with 8 GB of RAM.

4.1. The 10-bar truss

In Figure 3, the benchmark optimization problem of the 10-bar truss is depicted. The problem input data and constraints' limits are given as follows:

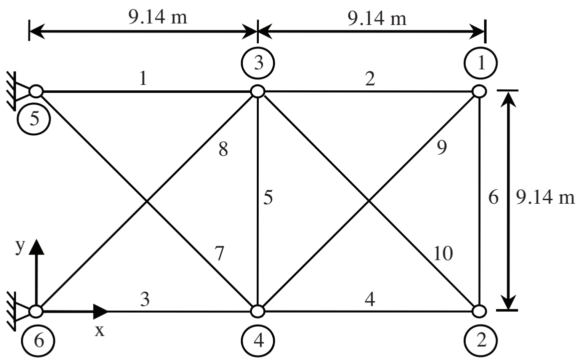

Figure 3. The 10-bar truss problem structure.

$\rho = 2.77 \times 10^3\ {}^{kg}/_{m^3}$ as the weight density,

$E = 6.9 \times 10^{10}\ {}^{N}/_{m^2}$ as Young's modulus,

$\sigma = \pm 1.72 \times 10^8\ {}^{N}/_{m^2}$ as the allowable stress for all members,

$d = \pm 5.08 \times 10^{-2}\, m$ as the displacement limit of each joint in the vertical direction.

The truss loading condition is considered as

$$P_{2y} = P_{4y} = -4.45 \times 10^5\, N$$

Cross-sectional areas of members are to be adopted among the numbers in the range from $6.45 \times 10^{-5} m^2$ to $2.26 \times 10^{-2}\, m^2$ with an increment equal to $5 \times 10^{-7} m^2$.

The problem in question is solved by the proposed AGA approach. The obtained optimal solution, outlined in Table 1, is achieved in 6.16 s. This solution meets all the design criteria; the structure weight associated with this solution is 2260 kg.

Table 1. Optimal solution of the 10-bar truss example.

Member	Cross-section (cm^2)	Member	Cross-section (cm^2)
1	197	6	0.645
2	0.645	7	51
3	180	8	125
4	87.9	9	124
5	0.645	10	0.645

Table 2 compares the solution obtained by AGA with those associated with some other existing methods. References associated with other solutions are cited in this table. Note that results associated with Perez and Behdinan (2007) correspond to various sorts of particle swarm optimization algorithm. Referring to Table 2, it is evident that the proposed AGA method is of an excellent optimality level, while its solution time is short as well.

Table 2. Comparison of solutions of the 10-bar truss example associated with various methods.

Method	Solution (kg)	Method	Solution (kg)
(Perez and Behdinan, 2007)	2280.99	(Memari and Fuladgar, 1994)	2261.42
(Perez and Behdinan, 2007)	2280.94	(El-Sayed and Jang, 1994)	2275.99
(Perez and Behdinan, 2007)	2280.99	(Galante, 1992)	2264.10
(Haftka and Gurdal, 1992)	2297.60	AGA	2261.42
(Adeli and Kamal, 1991)	2293.61	-	-

4.2. The 25-bar truss

The structure of the 25-bar problem is illustrated in Figure 4. The material properties including the design criteria are

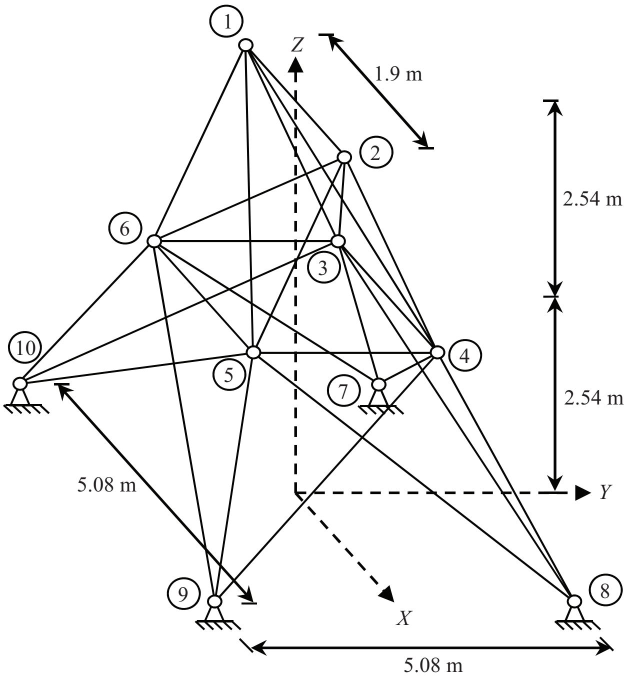

Figure 4. The 25-bar truss example.

$\rho = 2.77 \times 10^3 \ {}^{kg}/_{m^3}$ as the weight density,

$E = 6.9 \times 10^{10} \ {}^{N}/_{m^2}$ as Young's modulus,

$\sigma = \pm 2.76 \times 10^8 \ {}^{N}/_{m^2}$ as the allowable stress for all members,

$d = \pm 8.89 \times 10^{-3} \, m$ as the displacement limit of each joint.

In Table 3, the variable groups of the 25-bar truss structure are defined.

The truss loading condition is considered as follows:

$$P_{1x} = 4.45 \times 10^6 \, N, P_{1y} = P_{1z} = -4.45 \times 10^7 \, N$$

$$P_{2x} = 0 \, N, P_{2y} = P_{2z} = -4.45 \times 10^7 \, N$$

$$P_{3x} = 2.225 \times 10^6 \, N, \; P_{3y} = P_{3z} = 0 \, N$$

$$P_{6x} = 2.67 \times 10^{6}\, N,\; P_{6y} = P_{6z} = 0\, N$$

Cross-sectional areas of members are to be adopted among the numbers in the range from $6.5 \times 10^{-5} m^2$ to $2.26 \times 10^{-2}\, m^2$ with an increment equal to $1 \times 10^{-6} m^2$.

Table 3. Variable groups in the 25-bar truss.

Variable group	Members	Variable group	Members
1	1–2	5	3–4,5–6
2	1–4,2–3,1–5,2–6	6	3–10,6–7,5–8,4–9
3	2–4,2–5,1–6,1–3	7	4–7,3–8,5–10,6–9
4	4–5,3–6	8	6–10,3–7,4–8,5–9

As before, the above-described truss optimization problem is tackled by the proposed AGA approach. The problem solution is obtained in 17.5 s, and it is presented in Table 4. The total truss weight associated with the optimal solution is equal to 220 kg. In Table 5, the solution is compared with those of other methods reported in the literature. As can be seen, the solution obtained by AGA, even though it is reached in a very short time, has acceptable optimality compared with those of other approaches.

Table 4. Optimal solution of the 25-bar truss example.

Variable group	Cross-section (cm^2)	Variable group	Cross-section (cm^2)
1	0.65	5	0.65
2	6.58	6	3.99
3	21.93	7	13.24
4	0.65	8	21.93

Table 5. Comparison of solutions of the 25-bar truss example associated with various methods.

Method	Solution (kg)	Method	Solution (kg)
(Perez and Behdinan, 2007)	222.25	(Zhu, 1986)	255.57
(Perez and Behdinan, 2007)	220.34	(Wu and Chow, 1995)	220.78
(Perez and Behdinan, 2007)	219.66	(Erbatur et al., 2000)	224.19
(Zhou and Rozvany, 1993)	247.50	AGA	219.83
(Haftka and Gurdal, 1992)	247.53	-	-

4.3. The 72-bar truss example

This example, as demonstrated in Figure 5, is a 4-story 72-bar benchmark used in various studies to demonstrate the performance of the proposed optimization methods in a rather large structure. Here, we also examine the same example through AGA. In the 72-bar truss, the material properties including the design criteria are as follows:

$\rho = 2.77 \times 10^{3}\ {}^{kg}/_{m^3}$ as the weight density,

$E = 6.9 \times 10^{10}\ {}^{N}/_{m^2}$ as Young's modulus,

$\sigma = \pm 1.72 \times 10^{8}\ {}^{N}/_{m^2}$ as the allowable stress for all members,

$d = 6.35 \times 10^{-3}\, m$ as the displacement limit of each joint.

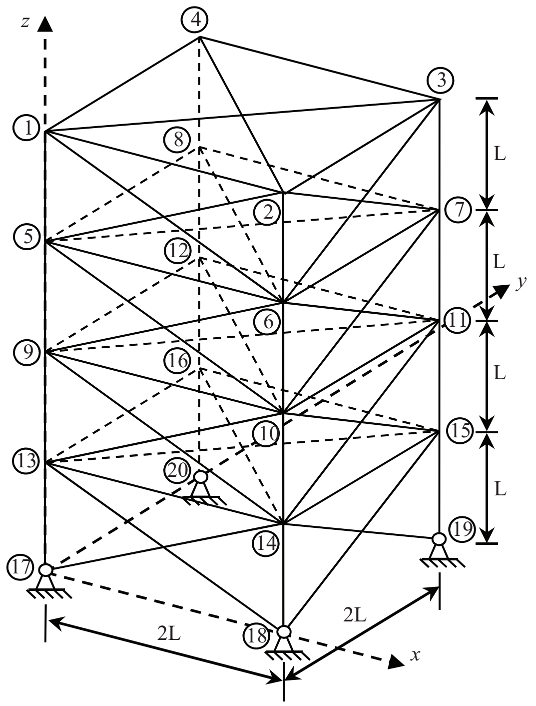

Figure 5. The 72-bar truss example.

In Table 6, the variable groups of the 72-bar truss structure are defined. The truss is subject to 2 loading cases as given in Table 7. Cross-sectional areas of members are to be adopted among the numbers in the range from $6.5 \times 10^{-5} m^2$ to $2.26 \times 10^{-2} m^2$ with an increment equal to $1 \times 10^{-6} m^2$.

Table 6. Variable groups in the 72-bar truss.

Variable group	Members	Variable group	Members
1	1–5,2–6,3–7,4–8	9	9–13,10–14,11–15,12–16
2	2–5,1–6,2–7,3–6, 3–8,4–7,4–5,1–8	10	9–14,10–13,10–15,11–14,11–16, 12–15,9–16,12–13
3	1–2,2–3,3–4,4–1	11	9–10,10–11,11–12,12–9
4	1–3,4–2	12	9–11,12–10
5	5–9,6–10,7–11,8–12	13	13–17,14–18,15–19,16–20
6	5–10,6–9,6–11,7–10,7–12,8–11,8–9,5–12	14	13–18,14–17,14–19,15–18,15–20, 16–17,13–20
7	5–6,6–7,7–8,8–5	15	13–14,14–15,15–16,16–13
8	5–7,8–6	16	13–15,16–14

The solution of the 72-bar truss optimization problem, tackled by the proposed AGA approach, is shown in Table 8. The execution time for this problem is about 49 s and the obtained solution is of 172 kg weight.

To assess the optimality of the AGA solution in this example, the solutions of some other techniques are outlined in Table 9. As before, Table 9 reveals that the proposed method outperforms most of the existing ones from the solution optimality aspect.

Table 7. Loading cases in the 72-bar truss [N].

Load case	Node	P_x	P_y	P_z
1	1	22,250	22,250	–22,250
2	1	0	0	–22,250
2	0	0	–22,250	0
3	0	0	–22,250	0
4	0	0	–22,250	0

Table 8. Optimal solution of the 72-bar truss example.

Variable group	Cross-section (cm^2)	Variable group	Cross-section (cm^2)
1	0.98	9	8.26
2	3.42	10	3.32
3	2.64	11	0.65
4	3.68	12	0.65
5	3.95	13	12.23
6	3.44	14	3.34
7	0.65	15	0.65
8	0.65	16	0.65

Table 9. Comparison of solutions of the 72-bar truss example associated with various methods.

Method	Solution (kg)	Method	Solution (kg)
(Perez and Behdinan, 2007)	172.99	(Erbatur et al., 2000)	175.14
(Perez and Behdinan, 2007)	173.39	(Schimit and Farshi, 1974)	176.44
(Perez and Behdinan, 2007)	172.47	(Gellatly and Berke, 1971)	179.77
(Zhou and Rozvany, 1993)	172.37	AGA	172.39

5. Comparison of AGA with GA

In this paper, comparison of the execution time associated with the proposed method and the other reported techniques is not conducted since this aspect strongly depends on the software coding skills and the machine hardware characteristics. However, since the most important feature of the proposed augmented method regards its execution time, this issue is elaborated in this section by illustrating the solution evolution in AGA and the 3 following methods:

(*i*) GA with consideration of the familial reproduction prohibition, we call it AGA1;

(ii) GA with the selection procedure based on the simulated annealing equation, it is denoted AGA2;

(iii) the canonical GA.

The 72-bar truss benchmark is examined for the sake of comparison. The optimal solution of this example was reported in Section IV.C. This solution was achieved by AGA after 60 generation evolution, as depicted in Figure 6. As can be seen in this figure, the objective function did not improve any further in the last 20 generations and that is why the optimization procedure stopped.

In Figure 6, the evolution histories of the other 3 methods until the generation number 60 are illustrated as well. Note that all these approaches reached to the optimal solution, after 159, 198, and 261 generations, respectively, for AGA1, AGA2, and GA. Figure 6 reveals that utilization of familial reproduction prohibition and the simulated annealing selection procedure led to a noticeable enhancement in the canonical GA technique.

Moreover, by comparing the evaluation trend of AGA1 and AGA2, one can deduce that the familial reproduction prohibition is more effective in the acceleration of AGA.

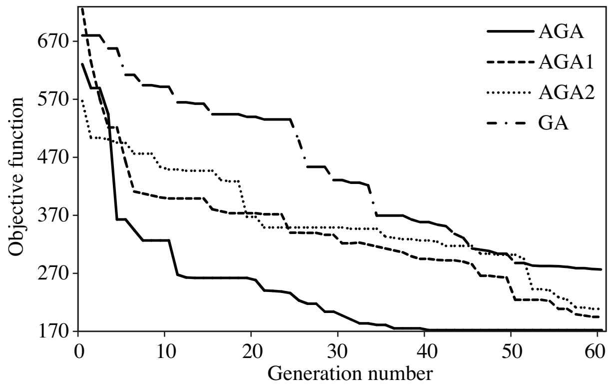

Figure 6. Evolution of solution in various algorithms.

6. Conclusion

This paper focused on the application of a new meta-heuristic optimization methodology, called AGA, in the design problem of steel trusses. The new method is an augmented version of GA in which an efficient selection procedure is employed and the familial reproduction of individuals is prohibited. Benchmark problems were also examined for the sake of verification of the new method's effectiveness. Based on the numerical evidence, the modifications applied in the GA have a considerable impact on its acceleration while the optimality of the solutions is not sacrificed. In addition, it is demonstrated that the proposed AGA outperforms most of the existing techniques from the optimality aspect. Separate investigations were performed to measure the effects of familial reproduction prohibition and the selection procedure based on simulated annealing. These studies demonstrated that the suggested familial reproduction prohibition contributes more to the acceleration of AGA. Application of the proposed AGA method in other fields of civil engineering might be promising and relevant efforts will very useful.

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