

Research Article

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Construction design based on particle group optimization algorithm

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Abstract: The machines exhibit an intelligence which is artificial intelligence (AI), and it is the design of intelligent agents. A system is represented by an intelligent agent who perceives its environment and the success rate is maximized by taking the action. The AI research is highly specialized and there are two subfields and each communication fails often. The popular AI approaches include the traditional symbolic AI and computational intelligence. In order to optimize the seismic design of the reinforced concrete pier structure, the particle swarm optimization (PSO) algorithm and the reaction spectrum analysis method are combined; they establish a regular bridge of the design variable with cross-sectional characteristics and reinforcement ratios, with the target function. The seismic optimization design framework of the pier is transformed into a multi-objective optimization problem. Calculations show that the method can quickly obtain the optimal design parameters that meet multi-objective requirements. The improved PSO main program and the calling push-over program run time are 4.32 and 1347.56 s, respectively; the push-over program running time is 99.68% of the run time of the total program. Optimization of the seismic performance of the rear bridge pier is significantly improved and is more in line with the design method; the design method proposed in this article is more practical.

Keywords: particle group optimization algorithm, structural optimization, steel frame, performance-based seismic design, reinforcement ratios, computational intelligence

1 Introduction

The particle group optimization algorithm is a global optimization algorithm inspired by the bird foraging behavior. Its main aim is to achieve the solution of the target problem through cooperation and information sharing between individuals. Compared to other evolutionary algorithms, the particle group algorithm is easy to implement and requires less parameters, strong robustness, and only small evolutionary groups, since the proposal is widely concerned by researchers. In the structural engineering, the particle swarm optimization (PSO) algorithm is applied to the optimized design of different structural systems. In these studies, the PSO algorithm is applied to the actual structural system seismic optimization design [1,2]. In order to apply the PSO algorithm to the structural seismic optimization design, steel frame is selected to optimize the design structure system, and the structural top-level displacement and interlayer displacement angle is used as performance indicator. It is constructed using a push-over seismic analysis method. In addition, in order to optimize the design of the seismic model, the PSO algorithm is introduced, and the PSO algorithm is improved by: (1) introducing a dynamic inertia weight, balanced algorithm development capabilities, and exploration capabilities; (2) updating particle speed when the global neighbor search is

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added to a certain neighborhood space, which increases the particle search range; (3) transmitting the continuous dispersion obtained by each iteration to the corresponding value discrete area when the particle position is updated, and the discussed solution is confirmed. Finally, by solving the three-layer four-sided steel frame, it is compared with the results of the relevant literature to evaluate the effectiveness of the steel frames with improved PSO algorithm [3,4].

In the structure design, an important role played by the optimization techniques is decision making. The maximum benefits are derived from the resources and the lighter construction and the effective structures are enabled while adequate safety levels are maintained [5]. A large scale of optimization techniques are suggested for the inherently complex problem solution posted in the design of structure. There is a wide variation of scopes depending upon the structural problem type that is to be tackled. In finding local optima, the gradient-based methods are very efficient when the design space is convex. A large number of design variables are involved in the problem design [6,7]. The local optimum will be a global optimum if the objective function is convex in nature. The design space convexity is impossible to check practically in the structural problems. Therefore, an obtained optimum assurance is the best possible among multiple feasible solutions. Highly nonlinear, non-convex design spaces are traversed by the non-gradient-based methods. The machines exhibit an intelligence which is artificial intelligence (AI), and it is the design of intelligent agents [8]. A system is represented by an intelligent agent who perceives its environment, and the success rate is maximized by taking the action. The AI research is highly specialized and there are two subfields and each communication fails often. The popular AI approaches include the traditional symbolic AI and computational intelligence (CI). CI is a set of nature-inspired computational methodologies which address the complex real-world problems to traditional approaches which are ineffective. The artificial neural network and evolutionary computation are included in CI [9,10]. The population of simple agents or boids is included in the SI systems and locally interacts with environment and each other. The nature, especially the biological systems, gives the inspiration for that and the agents follow very simple rules. The behavior of the individual agents is not dictated by the centralized control structure. The behavior of agents is local and such agents' interaction leads to the emergence of intelligent global behavior [11].

The organization of rest of the article is as follows. Section 2 provides an overview of the exhaustive literature survey, followed by a research methodology adopted in Section 3. The obtained results are discussed in Section 4. Finally, Section 5 concludes the article.

2 Literature review

Building energy-saving design issues can be solved in two phases. In the early stage, a large number of research studies mainly focused on problems such as energy consumption prediction models or strategies due to lack of effective simulation tools or the simulation tool operations and large-scale calculation costs. In recent years, with the increase in computer capacity, the speed of energy simulation software has become more fast and its calculation results are also more accurate, and scholars have begun to focus on model-based building energy optimization [12]. Some people collect this information from the project and build a model to find the best solution, and five projects in each project have ten possible solutions; PSO tries to find the best solution program. The results show that PSO is quite fast and found a best solution with high precision, and some problems have high effects [13,14]. It is proven to be a powerful and accurate loss in terms of construction issues, which can be used as other issues in other areas [4]. Jazayeri et al. uses an optimization method such as a metafor algorithm. As a case study, the ladder spill of India's tartar dam was considered and the improved particle swarm optimisation (IPSO) and the improved artificial bee colony (IABC) algorithms were used to obtain the optimum size of the spillway, and the results were compared with those of the Vittal and Porey (VP) method and other available results. The comparison of the results shows that the IABC and IPSO algorithms were increased by 17.72% when compared with the existing literature. In addition, when considering four: tepped spill, the results of IABC and IPSO algorithms have increased by

16.47 and 16.53%, respectively, compared with VP results [15]. The finding of maxima or minima of functions is concerned by the mathematical technique called optimization for a feasible reason. The optimization problems are solved by every business and industry so there are a variety of techniques which compete for better solution [16]. The new and modern technique is PSO, which performs well for the optimization problems. The global optimum solution is obtained for the complex space. In this article, the authors provide the review of PSO algorithm that helps the practitioner to improve the results. The theoretical idea and detailed explanation are detailed in this article; merits and demerits are also discussed by the authors. Moreover, the boundary conditions including discrete-valued problems, multi-objective PSO, and applications of PSO are also discussed. The particle swarm algorithm with its applications is introduced in this article with the optimal structure design. The heuristic particle swarm optimization (HPSO) is detailed based on the heuristic search schemes and the particle swarm algorithm [17]. The HPSO efficiency with the continuous variables and plates with discrete variables is compared, and HPSO implementation is presented in detail. The complex practical double-layer grid shell structure result shows the HPSO effectiveness. In this article, the authors detail a model-based technique which is an optimal design that can guide how to judiciously collect the data for making inference at low cost. For a statistical model, optimal design finding with several possibly interacting factors is challenging [18]. The nature-inspired metaheuristic algorithms are presented in this article and such optimization problems are solved. Such techniques are demonstrated and these techniques are implemented easily and different types of designs can be found. Such algorithm utilization facilitates generation of computer codes for tailor-made optimal design generation. The computing design efficiencies are also evaluated. As applications, the PSO is applied and a car-refuelling study is redesigned for Logistic model and some interacting factors. The ant colony algorithm and particle swarm algorithm are studied and developed in this article, and the combination of algorithm and architectural design is explored. The two algorithms' characteristics are also combined and realization way of intelligent algorithm is obtained in architecture design [19]. The algorithm rules are established for architectural design assistant. The foundation of ant colony algorithm is provided by the authors and the application range of intelligent algorithm is popularized. In this article, the authors provide simulation methods including particle systems as a material's model during numerical studies of building materials [20]. The single mathematical model cannot be utilized for the building material modeling at all levels of scale. However, some numerical methods are quite general and they can be used for modeling reinforcement regularities at micro- and nanoscale. The insight into regularities of structure is offered by the obtained results which allow the time and cost reduction.

2.1 Contribution

The seismic design of the reinforced concrete pier structure, the PSO algorithm, and the reaction spectrum analysis method are combined for optimization, establishing a regular bridge of the design variable with cross-sectional characteristics and reinforcement ratios, with the target function. The seismic optimization design framework of the pier is transformed into a multi-objective optimization problem.

3 Research methods

3.1 Seismic optimization model

Performance-based seismic design idea is an important stage of development of building structures. Based on performance-based seismic design ideas that enable design structures to maintain the desired performance level under earthquake action, the performance goals such as stress level, load, displacement, limit

status, and target injury indicators are not transcended. The push-over analysis method is one of the important methods of assessing the seismic performance of the structure. This method is essentially a static elastoplastic analysis method combined with the reaction spectrum, which has a weak part of the discovery structure, which is intuitively judging the structure. The authors use the relevant provisions of the American seismic design specification FEMA-273 and FEMA-350 and the push-over seismic analysis method to perform steel frame structural seismic optimization design with the structural top-level displacement and interlayer displacement angle [21–25].

3.1.1 Target function

In steel frame design, the lighter the weight of the structure, the less the material consumed, and the lower the general engineering cost. At the same time, the weight reduction of steel frames can also reduce the basis of load [26,27]. Therefore, under the premise of the steel frame beam and column node connection, the total mass of the steel frame structure is minimized, and the target function is established:

$$\min W = \sum_{i=1}^n \rho_i A_i L_i, \quad (1)$$

where ρ_i , A_i , and L_i is the density, cross-sectional area, and length of the steel member i , respectively.

3.1.2 Constraint

Engineering practice shows that the mild lateral displacement caused by earthquake effects may lead to unstructured damage of people in psychological discomfort, while the excessive nonelastic deformation caused by strong earthquakes is often possible to make the building and architecture around the building. Therefore, in the seismic design process, it is necessary to consciously control the construction site displacement within the scope of the specification.

Federal Emergency Management Agency (FEMA-273) divides structural seismic properties into different categories [28–33]. The lateral displacement is taken from 0.4, 0.7, 2.5, and 5%, and the structural nodes do not allow plastic deformation before the first-grade (normal use) performance state. In addition, the FEMA-350 specifies 1.25 and 6.1%, respectively, at the second and fourth performance levels. Specific four kinds of performance levels under constraints are as follows:

$$\text{OP level: } \Delta^{\text{OP}} \leq 0.4\%H, \quad (2)$$

$$\text{IO level: } \Delta^{\text{IO}} \leq 0.7\%H, \theta^{\text{IO}} \leq 1.25, \quad (3)$$

$$\text{LS level: } \Delta^{\text{LS}} \leq 2.5\%H, \quad (4)$$

$$\text{CP level: } \Delta^{\text{CP}} \leq 5\%H, \theta^{\text{CP}} \leq 6.1, \quad (5)$$

where Δ^{OP} , Δ^{IO} , Δ^{LS} , and Δ^{CP} are the structures in the four performance states, respectively; θ^{IO} and θ^{CP} are the structures in the second and fourth performance states, respectively.

3.1.3 Constraint

In the earthquake optimization model of the steel frame, the ultimate object is to obtain the optimal cross-section type of each steel member in the case of satisfying the constraint. In the characteristics of the particle group algorithm, it is necessary to make the target function value (each steel member quality). It continuously decreases in particle evolution iteration. Therefore, iterative process is the best solution which is prematurely abandoned due to slight violation of the constraints. By using this approach, the entire

particle group can lost the potential guidance. In order to overcome the above problems, a penalty function processing mechanism is selected [34–36]. The method achieves a proper punishment of those slightly illegal constraints by appropriate λ_1 and λ_2 , but not completely “killing” effect. Make these solutions still have the opportunity to go optimal or better in subsequent iterations. The penalty function of this method is set to:

$$F = W \times (1 + \lambda_1 V)^{\lambda_2}, \quad (6)$$

where F is a penalty function; λ_1, λ_2 is a penalty factor; V is the overall constraint extent of the structure, and its expression is as follows:

$$V = V^{OP} + V^{IO} + V^{LS} + V^{CP} + \theta^{IO} + \theta^{CP}. \quad (7)$$

3.1.4 Push-over calculation analysis method

The idea of the push-over calculation analysis is to borrow the concept of the elastic system to decompose the reactive spectrum, and the horizontal earthquake force under the respective vibration type is applied to the structure, which in turn gradually pushes the structure to a given target [37–39]. The displacement is to study the nonlinear performance of the structure, thus determining whether the structure and component deformation force satisfy the design requirements. Selecting a reasonable load mode in the push-over analysis method is a key problem. Typical loading mode has a uniform loading; inverted triangle loading is shown in Figure 1. When the earthquake optimization structure model is rules and height, the effect of high vibration type can be ignored, and only the first vibration type is considered. Since the verification example is a three-layer four-schogene frame structure, a horizontal loading mode for push-over analysis can be selected. In order to unify the comparative literature, the index load model is used, and the level load calculation applied is as follows:

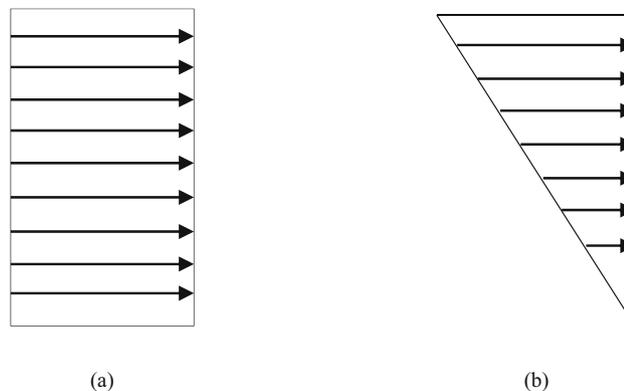


Figure 1: Schematic diagram of horizontal loading mode: (a) uniform loading and (b) inverted triangle loading.

$$P_x = \frac{W_x h_x^k}{\sum_{i=1}^n W_i h_i^k} \cdot V_b, \quad (8)$$

where P_x is the level x load; W_x, W_i is x, i -layer gravity load representation value; h_x, h_i is x, i , respectively, the height of the ground surface; n is the total layer of structure; k is the parameter related to the basic cycle here $K = 2$; and V_b is the bottom shear of the structure.

3.2 Particle four optimization algorithm improvement

3.2.1 Inertial weight

Shi and Eberhart have first proposed the concept of inertia ω , and the selection of particles can be greatly controlled by suitable inertia weight ω , allowing particles to keep the moment of inertia, so that their search space is expanded, thereby organizing in the new area and exploring the optimal solution. In order to apply the PSO algorithm to structural optimization design, an introduction of a dynamic inertia weight is as follows:

$$\omega_{iter} = \omega_{min} + (\omega_{max} - \omega_{min}) \times e^{\left[-k \times \left(\frac{iter}{iter_{max}}\right)^u\right]}, \tag{9}$$

where ω_{max} , ω_{min} is the inertial weight, lower limit; $iter_{max}$ is the maximum number of iterations; $iter$ is the current iteration of particles; and k , u is the test constant. As shown in Figure 2, the method is taken from k , u in the integrated control formula. Figure 2 shows three situations: $k = 5, u = 10$; $k = 10, u = 10$; $k = 10, u = 5$. It can make the particle group to obtain greater inertia weight in the previous period to broaden the particle search space, and the medium-term inertia weight loss is faster, improves the algorithm search efficiency, and later takes less inertia weight to facilitate particles to perform fine development near the best solution [35,36].

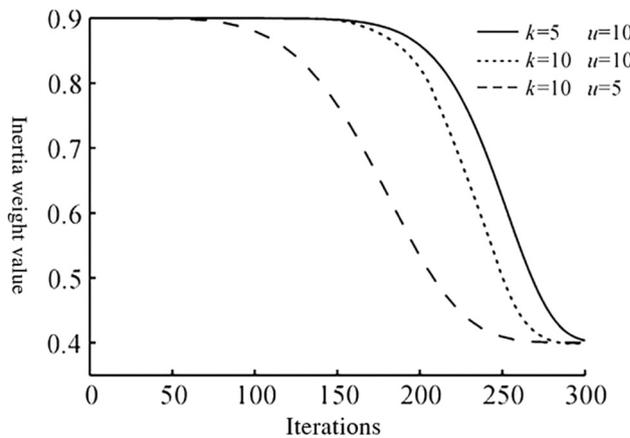


Figure 2: Dynamic inertia weight.

3.2.2 Speed update

In the standard particle group algorithm position update, the new particles are only booted by the optimal position of the determined individual and the current global optimal position, ignoring the optimal position that may exist in the neighborhood interval, so the standard particle group is easy to fall into local optimal. A modified particle group speed update formula is used for standard particle group defects. The formula adds a certain neighboring space in the global neighborhood search, which is interspent in the optimal position and the current global optimal position, and the original value of Δ is stepped, and two domain intervals, $[P_{ibest,j}^t(1 - \delta U(0, 1)), P_{gbest,j}^t(1 + \delta U(0, 1))]$ and $[P_{gbest,j}^t(1 - \delta U(0, 1)), P_{ibest,j}^t(1 + \delta U(0, 1))]$, are formed. The algorithm makes the neighborhood random search in the set interval and effectively increases the search range, and its calculation is as follows:

$$v_{i,j}^{t+1} = \omega_t v_{i,j}^t + c_1 r_1 [P_{ibest,j}^t(1 + \delta U(0, 1)) - x_{i,j}^t], \tag{10}$$

$$x_{i,j}^{t+1} = x_{i,j}^t + v_{i,j}^{t+1}, \tag{11}$$

where t is the particle evolutionary generation; c_1, c_2 is a cognitive factor and a social learning factor; r_1, r_2, U (0,1) is a uniform distribution random number on the interval (0, 1); δ is a disturbance factor; P_{ibest} is the most excellent; and P_{gbest} is the overall optimal.

3.2.3 Value discretization

Standard particle group algorithm has high applicability for continuous problems, and for discrete problems, it is often necessary to correct the standard particle group algorithm. The design variable in the steel frame optimization model is 274 H-shaped steel in the American steel structure steel sheet, so the continuous solution obtained by each iteration of the particle population is required to be treated with 274 H-type steel using the standard particle group algorithm. The PSO algorithm should be improved to introduce a

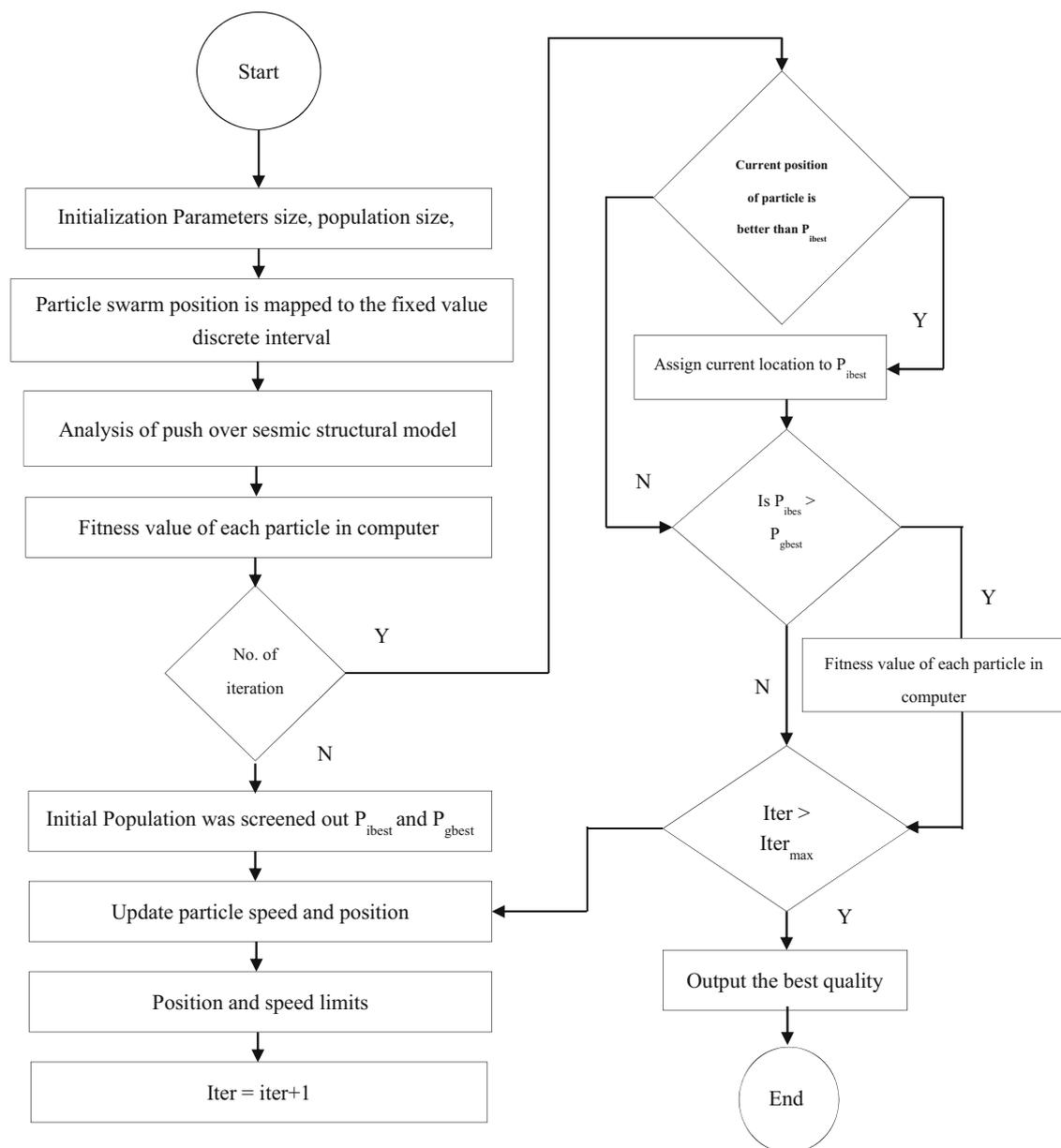


Figure 3: Flow chart of steel frame seismic optimization design based on improved particle swarm algorithm.

method of solving the emissive discrete area in the iterative process, which still uses the speed and position iteration formula of consensus and the particles each time the position obtained after the iteration is compared with 274 kinds of H-type steel cross-sectional area, and each element in the position vector is taken as the closest type steel cross-sectional area. Steel frame optimization design flow based on improved PSO algorithm is shown in Figure 3.

4 Results and discussion

The results and the seismic optimization model example of three-layer four-sided steel frame are shown in Figure 4. In the model, the steel frames are divided into five groups, and the same set of steel components uses the same type steel; the steel elastic modulus is 200 GPa and the density is 7,849 kg/m³. The yield strength of the frame beam and the column is 339,397 MPa, respectively. Heat live load combination after the distribution, 32 kN/m of 32 kN/m, is applied to the structure, and a line load is applied to the top layer. In addition, the weight of the seismic design of the first and second layers is 4,688 kN, and the top seismic design is 5,071 kN.

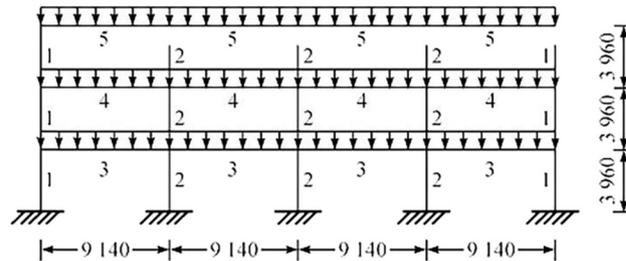


Figure 4: Three-layer four-span steel frame.

In this example, the parameters of the PSO algorithm are improved to $\lambda_1 = 0.9$, $\lambda_2 = 2$, $\omega_{max} = 0.9$, $\omega_{min} = 0.4$, $iter_{max} = 200$, $k = 10$, $u = 5$, $c_1 = c_2 = 2$, and $\delta = 0.01$. Preparation improves the PSO algorithm Matlab main program, with the top-level displacement angle of the steel frame as a performance index using the push-over program to seismically analyze the structure, and the steel framework example is based on performance-based structural seismic optimization design.

Under the same constraint, the random pair of ten optimization tests is considered. Figure 5 shows the specific results obtained by ten optimization tests. Table 1 takes the best results and the worst results and compares with other literature results.

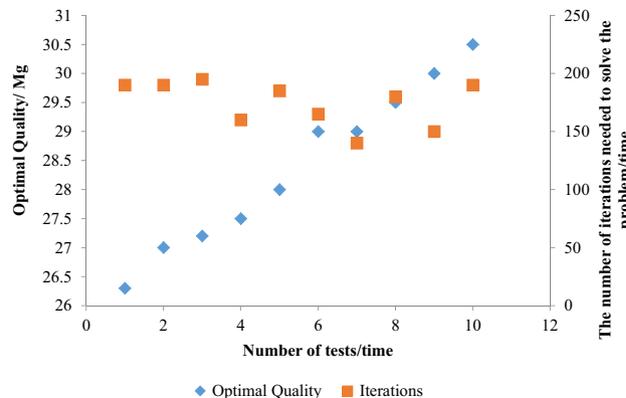


Figure 5: Improved PSO algorithm ten optimization test results.

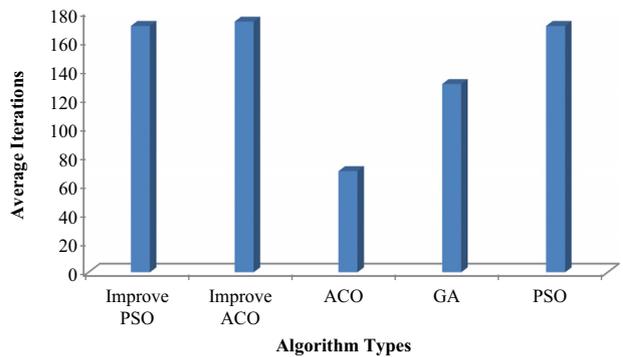
Table 1: Optimization results and initial design contrast

Algorithm	Comparison of optimization results and initial design									
	Building groups			Optimal quality/kg	Average quality	Maximum quality/kg	Standard difference/kg	Average number of iterations/times	Number of analyses/times	
Initial design	W14X257	W14X311	W33X118	W30X116	W24X68	42,077				
Improvement PSO	W30X116	W30X116	W33X118	W33X118	W24X62	26,505	1,250	173		865
Improvement ACO [12]	W33X152	W30X130	W27X102	W33X118	W14X68	27,983	758	177		865
ACO [7]	W33X118	W40X183	W24X131	W8X28	W30X16	28,793	772	78		3,900
GA [7]	W12X45	W40X235	W18X86	W14X90	W36X135	30,985	1,461	136		6,800
PSO [13]						29,214	1,067	170		8,500

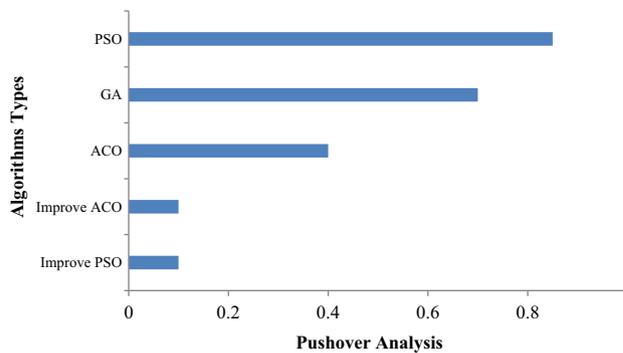
Table 2: Optimal deactivation structure seismic property level

Algorithm	OP	IO	LS	CP	IO	CP
Performance Requirements [5,6]	4.75	8.32	29.72	59.44	1.25	6.10
Improvement PSO	3.34	6.13	7.36	27.77	0.59	2.47
Improvement ACO [12]	3.56	6.48	7.81	43.87	0.66	3.92
ACO [12]	4.23	7.62	9.11	51.05	0.81	4.64
GA [7]	4.35	7.81	9.38	57.61	0.88	5.09

The amount of steel in the optimized results is shown in Tables 1 and 2, and it can be seen that the improved PSO algorithm is significantly higher than that of the PSO algorithm. The optimal quality of steel obtained by random optimization of the improved PSO algorithm for ten times is 26,505 kg, which is only 62.99% of the steel used in the initial design. Compared with the optimization results obtained by the improved ant colony optimisation (ACO) [12], ACO [7], PSO [13], and genetic algorithms (GA) [7], 1,478, 2,288, 2,709, and 4,480 kg of steel are saved, respectively. From ten test optimization, the amount of steel and maximum use of steel improved the PSO algorithm, which also exhibited a huge advantage and improved the average steel capacity of 28,433 kg, lower than comparison optimization algorithm. The average amount of steel obtained by 10× is lower than the three optimal qualities of the three optimization algorithms of PSO, ACO, and GA. Figure 6 shows a comparative situation of improving the average iterative number of PSO algorithms and several comparative algorithms and the number of push-over analysis. The average number of iterations of the improved PSO algorithm is 173×, compared to the PSO algorithm, the GA algorithm, and the ACO algorithm, and is 33,795 iterations, which is less than the improved ACO algorithm. Single number of iterations is compared to the three algorithms of PSO, ACO, and GA, which do not seem to have advantage



(a)



(b)

Figure 6: (a) Average number of iterative times and (b) the number of push-over analysis.

compared to the three algorithms of PSO, ACO, and GA, resulting in this three-algorithm optimization procedures $M = 50$; therefore, the algorithm is an iteration of each cycle which requires 50 push-over analysis. Select the number of optimized individuals and add population richness, which is conducive to optimizing individual traversal solutions. When the improved algorithm is updated in the particle speed, a certain neighbor space is added to the global neighborhood search, increasing the particle optimization range; through the appropriate penalty function mechanism, add some potential to the entire population in the iterative process. Thus, the number of particles in the improved algorithm does not need to be set, and the number of particles in the verification example is 5. By carrying out 200 iteration tests on the optimization program: about 1351.88 s of the entire optimization program, the improved PSO main program and the calling push-over program run time are 4.32 and 1347.56 s, respectively; the push-over program running time is 99.68% of the run time of the total program. The number of optimized individuals selected means that the number of push-over analysis is high, causing an increase in the operation time of the entire optimization program. While ignoring the main program runtime, the average search solution time to improve the PSO algorithm is only 13.72% whereas in the ACO algorithm it is 60.48%, therefore, it is required to improve the PSO algorithm for the efficiency and optimal solution.

Figure 7 shows an iterative process curve that improves the PSO algorithm in solving the optimal solution, thereby causing that the improved PSO algorithm can quickly converge to the optimal solution in the near future, thereby performing an accurate search around the optimal solution.

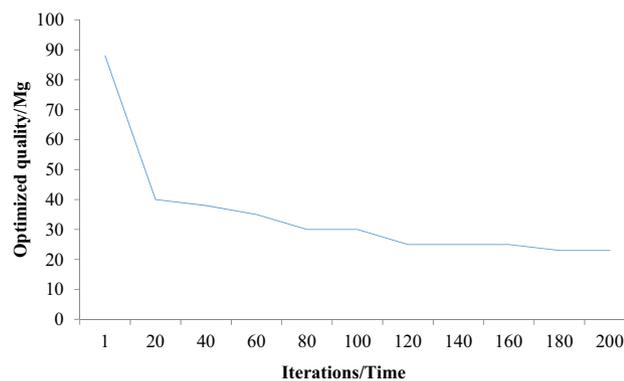


Figure 7: Optimized iterative curve.

Table 2 shows the top-level displacement and interlayer displacement angle indicators of improved PSO algorithm and comparison with different seismic performance levels. It is also presented graphically in Figure 8 for better analysis. The horizontal displacement and displacement angle of the optimal decompression structure are within the specified range, and the improved PSO algorithm is applied to the three-layer four-step steel frame optimization design compared to several compared algorithms. The horizontal displacement and displacement angle of each layer are smaller. Therefore, the improved algorithm is allowed to save design materials as well as seismic performance of steel frame in the optimization model.

Figure 9 shows the push-over curve of an equivalent seismic load-top displacement of the optimal interpretation structure, and Figure 9 shows the plastic development conditions in the frame of each of the four grades of performance target. Before the OP performance state, all the components of the frame are in the elastic phase. The load and the top level are shifted into linear relationship. The top frame beam node is first achieved by the increase in structural equivalent seismic loads and exhibits plastic deformation.

After the immediate occupancy (IO) state, the under layer begins to show plastic deformation. With the further increase in structural equivalent seismic loading, the top-level displacement is rapidly increased, and somewhere of the beam member enters the plastic state and the plasticity of the nodes in the three columns; this beam-string plastic development process is just the concept of “strong pillars” in the structural design. By quantitative calculations, it was found that the top-level displacement increment of the

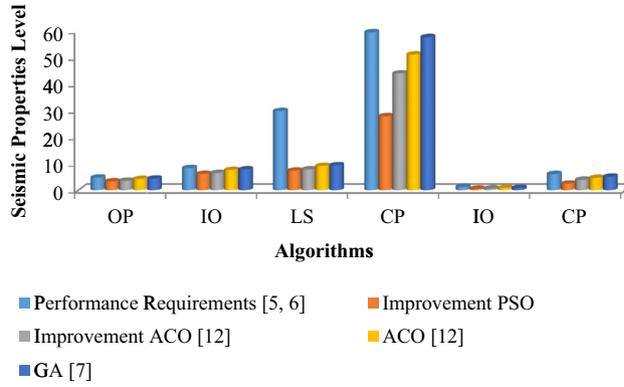


Figure 8: Structure seismic property level.

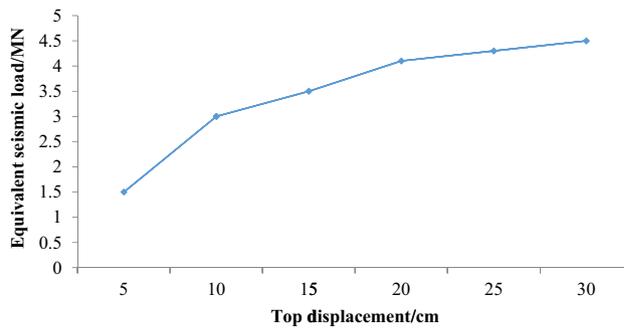


Figure 9: Push-over curve.

limit space (LS) to the crystal plasticity (CP) segment reached six times more of the total displacement of the elastic phase.

5 Conclusion

A large scale of optimization techniques are suggested for the inherently complex problem solution posted in the design of structure. There is a wide variation of scopes depending upon the structural problem type that is to be tackled. Compared to other evolutionary algorithms, the particle group algorithm is easy to implement and requires less parameters, strong robustness, only small evolutionary groups, etc., since the proposal is widely concerned by researchers. Three aspects of the inertial weight value, speed update method, and location update methods are improved, and the stability, solving speed, and solving quality of particle group algorithm are improved; the reasonable penalty function mechanism solves the particle group algorithm and has some potential to solve populations frequently in the iterative process; a three-layer four-step steel frame example indicates that the applicability and effectiveness of PSO design in structural seismic optimization design can be applied to steel frame seismic optimization design. The improved PSO main program and the calling push-over program run time are 4.32 and 1347.56 s, respectively; the push-over program running time is 99.68% of the run time of the total program. The horizontal displacement and displacement angle of the optimal decompression structure are within the specified range, and the improved PSO algorithm is applied to the three-layer four-step steel frame optimization design compared to several compared algorithms. The optimization of improved particle swarm algorithm applications to optimal structure design will be the future concern of this work.

Conflict of interest: Authors state no conflict of interest.

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