



HYBRID PARTICLE SWARM OPTIMIZATION, GRID SEARCH METHOD AND UNIVARIATE METHOD TO OPTIMALLY DESIGN STEEL FRAME STRUCTURES

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ABSTRACT

This paper combines particle swarm optimization, grid search method and univariate method as a general optimization approach for any type of problems emphasizing on optimum design of steel frame structures. The new algorithm is denoted as the GSU-PSO. This method attempts to decrease the search space and only searches the space near the optimum point. To achieve this aim, the whole search space is divided into a series of grids by applying the grid search method. By using a method derived from the univariate method, the variables of the best particle change values. Finally, by considering an interval adjustment to the variables and generating particles randomly in new intervals, the particle swarm optimization allows us to swiftly find the optimum solution. This method causes converge to the optimum solution more rapidly and with less number of analyses involved. The proposed GSU-PSO algorithm is tested on several steel frames from the literature. The algorithm is implemented by interfacing MATLAB mathematical software and SAP2000 structural analysis code. The results indicated that this method has a higher convergence speed towards the optimal solution compared to the conventional and some well-known meta-heuristic algorithms. In comparison to the PSO algorithm, the proposed method required around 45% of the total number of analyses recorded and improved marginally the accuracy of solutions.

Keywords: particle swarm optimization; grid search method; univariate method; steel frame structures.

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1. INTRODUCTION

Designing steel frames optimally is an important task for structural designers in today's market with dwindling resources [1, 2]. The aim of steel frame design optimization is usually to minimize the frame weight [3-6] while being subject to drift constraints and code-specified strength. The design variables are cross-sections of columns and beams chosen from standard cross-sections provided in the steel construction manual [4, 7]. Two general methods have been introduced for optimization problems: classical methods and heuristic approaches [8]. Classical optimization methods required gradient information of the objective function and constraints, where the final results depend on the initially selected points [1, 8].

Because of the drawbacks of classical method, researchers have devised more flexible and adaptable methods. Thus, meta-heuristic techniques have been developed by researchers. They do not require gradient information and possess better global search than the classical methods [8]. These methods are typically inspired by natural or physical phenomena such as genetic algorithms (GAs) [9], taboo search (TS) [10], ant colony (ACO) [11], particle swarm (PSO) [12], simulated annealing (SA) [13], harmony search (HS) [14] and big bang-big crunch (BB-BC) [15]. Particle Swarm Optimization (PSO) is an important branch of meta-heuristic algorithms. Due to having simple concepts, few parameters, and being far distant from computational features, it has been extensively applied in structural optimization problems [16-22].

In this paper, the implementation of an efficient hybrid algorithm based on particle swarm optimization, grid search method and univariate method, namely (GSU-PSO), is developed in order to improve the convergence speed of response of the PSO algorithm. The remainder of the paper is organized as follows: Section 2 presents the formulation of the steel frame design optimization problem according to AISC-LRFD [23] while Section 3 describes the particle swarm optimization technique, grid search and univariate method. The steps of the GSU-PSO for optimization of frames are outlined in Sections 4 and 5 which compare optimization results with the standard PSO and other methods documented in the literature. Finally, the important conclusions of this study are summarized in Section 6.

2. FRAME OPTIMIZATION PROBLEMS TO AISC-LRFD

The aim of the optimum design of steel frames is to find a design with minimum weight. Total weight of the frame structure can be expressed as:

$$f(X) = \sum_{i=1}^{nm} \gamma_i \cdot x_i \cdot l_i \quad (1)$$

where γ_i is the material density of i-th member; l_i is the length of i-th member and nm is the number of members making up the frame. According to AISC-LRFD [23] code of practice, weight structure is subjected to several design constraints. These constraints contain:

Element stresses

$$v_i^\sigma = 1 - \frac{\sigma_i}{\sigma_i^a} \leq 0 \quad i = 1, 2, \dots, nm \quad (2)$$

Maximum lateral displacement

$$v^\Delta = R - \frac{\Delta_T}{H} \leq 0 \quad (3)$$

Inter-story displacements

$$v_j^d = R_I - \frac{d_j}{h_j} \leq 0 \quad j = 1, 2, \dots, ns \quad (4)$$

where σ_i and σ_i^a are the stress and allowable stress in i -th member, respectively; R is the maximum drift index; Δ_T is the maximum lateral displacement; H is the height of the frame structure; d_j is the inter-story drift; h_j is the story height of the j -th floor; ns is the total number of stories; R_I is the inter-story drift index permitted by the code of practice. According to the AISC [23], the allowed inter-story drift index is given as 1/300, and the LRFD interaction formula constraints (AISC, Equation H1-1a,b) are stated as:

$$v_i^I = 1 - \frac{P_u}{2\phi_c P_n} - \left(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}} \right) \leq 0 \quad \text{For } \frac{P_u}{\phi_c P_n} < 0.2 \quad (5)$$

$$v_i^I = 1 - \frac{P_u}{\phi_c P_n} - \frac{8}{9} \left(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}} \right) \leq 0 \quad \text{For } \frac{P_u}{\phi_c P_n} \geq 0.2 \quad (6)$$

where P_u is the required strength (tension or compression); P_n is the nominal axial strength (tension or compression); ϕ_c is the resistance factor ($\phi_c = 0.9$ for tension, $\phi_c = 0.85$ for compression); M_{ux} and M_{uy} are the required flexural strengths in the x and y directions; respectively; M_{nx} and M_{ny} are the nominal flexural strengths in the x and y directions (for two-dimensional structures, $M_{ny} = 0$); and ϕ_b is the flexural resistance reduction factor ($\phi_b = 0.90$).

The effective length K to compute compression and Euler stresses factors are required. For beam and bracing members, K is taken equal to unity. For column members, K values are calculated by SAP2000 as follows:

For unbraced members:

$$K = \sqrt{\frac{1.6 G_A G_B + 4(G_A G_B) + 7.5}{G_A + G_B + 7.5}} \geq 1 \quad (7)$$

3. REVIEW OF PARTICLE SWARM OPTIMIZATION TECHNIQUE, GRID SEARCH METHOD AND UNIVARIATE SCHEME

Since GSU-PSO methodology is based on PSO, grid search and univariate method, the specifications of these methods are briefly explained in this section.

3.1 Particle swarm optimization

Particle Swarm Optimization is a meta-heuristic technique. The basic idea was introduced by Eberhart, computer scientist, and Kennedy, an expert in the field of social psychology in 1995 [12]. PSO algorithm is based on the production of a random population inspired by social behavior of animals such as bird flocking or fish schooling. The population is called a swarm and each member of the population is called a particle [12, 24, 25]. The basic idea of PSO is that each particle is moved in search space to find the optimum point, and the best situation, that is, the best individual position of the particle, in the various stages is stored; this value is called ($P_{best,i}$) at each step of the search. Particles exchange information about the situation to help each other to find the optimal situation: each particle uses a particle which has the best match (that is, the best global situation of the community (G_{best}) to adjust its pace). After finding the two best values, the particle updates its velocity and positions according to the following formula [12, 24]:

$$V_{ij}^t = \omega V_{ij}^{t-1} + c_1 r_1 (P_{best,ij}^{t-1} - X_{ij}^{t-1}) + c_2 r_2 (G_{best,i}^{t-1} - X_{ij}^{t-1}) \quad (8)$$

$$X_{ij}^t = X_{ij}^{t-1} + V_{ij}^t \quad j = 1, 2, \dots, d \quad i = 1, 2, \dots, n \quad (9)$$

where V_{id}^{t-1} , V_{id}^t and X_{id}^t are the velocity vector in the previous cycle, the velocity vector in the current cycle and the position vector of particle i in the current cycle along the d -th dimension, respectively. $P_{best,i}^t$ is the best position in the history of particle i along the d -th dimension in cycle t . G_{best}^t is the best position in the history of all the particles along the d -th dimension in cycle t . c_1 and c_2 are acceleration coefficients. r_1 and r_2 are two independent random numbers uniformly distributed in the range of $[0, 1]$. ω is the inertia weight factor.

3.2 Grid search method

In this method a suitable grid in the design space is produced, then the objective function is evaluated at all the grid points, eventually the grid point corresponding to the lowest function value is selected. For example, if l_i and u_i are known as the lower and upper bounds on the i -th design variable, respectively, the range (l_i, u_i) can be divided into $p_i - 1$ equal parts so that the grid points along the x_i axis denote $x_i^{(1)}, x_i^{(2)}, \dots, x_i^{(n)}$ ($i = 1, 2, \dots, n$). In Fig. 1 a grid in a two-dimensional design space with $p_i = 4$ is shown. The grid method requires a large number of functions calculated in most practical problems. For example, for a problem with 10 design variables ($n=10$) and $p_i = 3$ the number of grid points will be $3^{10} = 59049$. Therefore, the grid method can be used to find an approximate minimum for problems with a small number of design variables. Also, this method can be used to find a good starting point for one of the more efficient methods [26].

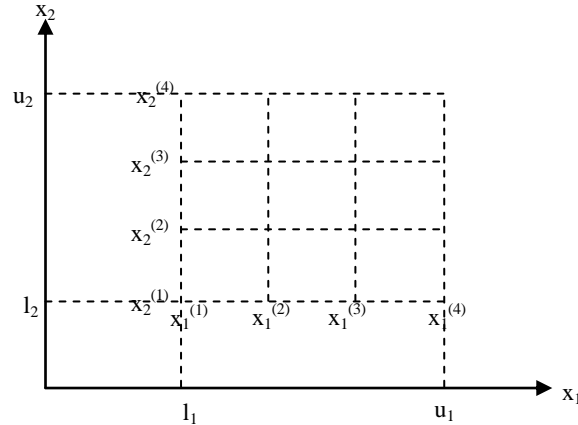


Figure 1. Grid with $p_i=4$ [26]

3.3. Univariate method

This method deals with only one variable change at a time and seeks to produce a sequence of improved approximations to the minimum point. By starting at a base point X_i in the i -th iteration, the values of $n - 1$ variables are fixed and the remaining variables are modified. Since only one variable is modified, the problem becomes a one-dimensional minimization problem. The first cycle is completed after all the n directions are searched sequentially, and then the entire process of continuous minimization is repeated. The procedure is continued until no further improvement is possible in the objective function in any of the n directions of a cycle.

The univariate method will not converge rapidly to the optimum point as it has a tendency to oscillate with steadily decreasing progress toward the optimum. Hence, it will be better to stop the computations at some point near the optimum point [26].

4. HYBRID PSO, GRID SEARCH AND UNIVARIATE METHODS

GSU-PSO algorithm is designed in two phases. In the first phase, by utilizing a method derived from the grid search method the feasible region is identified. Then the global optimum was approached using a method derived from the univariate method and, as long as the change in variables cause violation of constraints, the variables of the best design are changed one after another. To describe the methodology of the first phase, a flowchart is given in Fig. 2. In the second phase, global optimum is searched by using PSO with considering an interval close to the variables and generating random particles in new intervals. These concepts will be explained in detail in Sections 4.1 to 4.7.

4.1 Sorting the catalog of design variables

In order to minimize the weight of structure in case discrete sections such as W-Section are used, cross-sections should be sorted according to their surface.

4.2 Gridding search space

In this section, an effective method is introduced to evaluate the search space. In this method it is assumed that the search space can be divided into a series of grids using the grid search method. In grid search method a suitable grid in the design space is produced and then objective function is evaluated at all grid points until the lowest function value is found. The disadvantage of this method is that if the number of variables increases, the number of grid points would decrease. In order to overcome these shortcomings, a survey was carried out. After gridding the search space, only the grid areas positioned on diagonal search space are searched which only produce one particle. Then, using a method derived from a univariate method the variables of the best particle were changed. Moreover, the volume of computing grid search is reduced. It will also lead to determining the near global optimum solution in a least amount of analyses required. Concepts expressed are shown in Fig. 3.

4.3 Generating random design

After gridding design space, only a random particle is produced in each of the diameter grids and the corresponding objective function is calculated.

4.4 Choosing best design

After only a random particle is produced in each of the diameter grids, the objective function is calculated. The particle with the lowest objective function without constraints violation is selected and the remaining particles are deleted.

4.5 Determining the direction of desired movement for variables

Two direction of movement for each variable is created: 1- direction of movement towards an increase in the value of the variable, 2- direction of movement towards a decrease in the value of the variable.

To determine the desired direction for the first variable, objective function and violation of constraints are calculated for changes in the value of the first variable that are $f(d \pm e)$ and $V(d \pm e)$. d , f and V are equal to the best design obtained in Section 4.4, objective function and violation of constraint, respectively. e is equal to the length step change in the value of the variables. By comparing two values of the objective functions $f(d + e)$ and $f(d - e)$, the direction in which the improved objective function with zero violation of constraints is selected. This process continues until the desired direction for all variables are determined.

4.6 Changing the value of variables to improve the objective function

After determining the desired direction for all variables, the values of variables are changed to improve the objective function. This section was inspired from univariate method. In this method, the first variable is changed and other variables are kept constant. Then objective function and violation of constraints are calculated. Although the objective function is improved and violation of constraint is zero, the value for the first variable is considered. Otherwise, the value of first variable is equal to the previous value. This process is repeated for all the variables until the change in the value of variable would cause violation of

constraint or the objective function would not further improve.

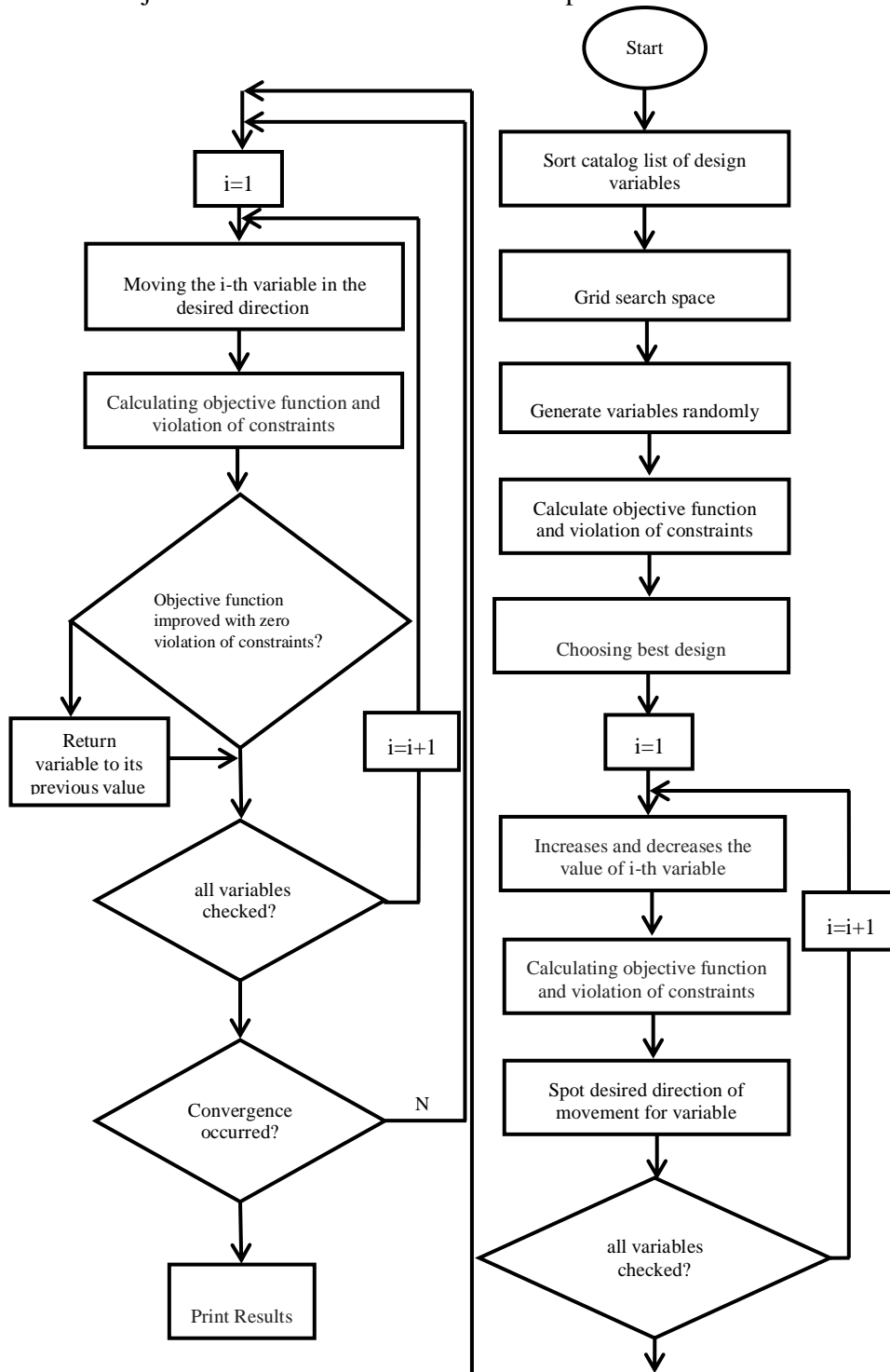


Figure 2. Flowchart of the first phase of GSU-PSO

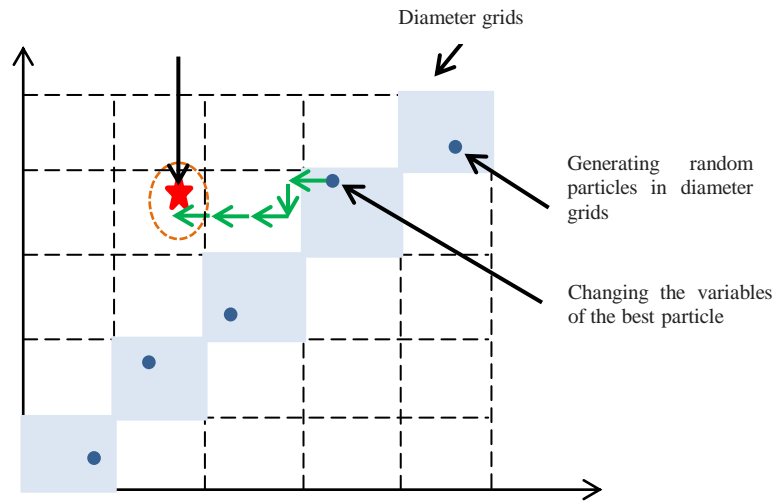


Figure 3. displaying two-dimensional design space

4.7 Entering data into PSO algorithm

To use PSO algorithm, a set of random numbers is generated. Using the variables obtained in Sections 4.6 and taking into consideration an interval close to the variables, the new domain of variables is generated to produce random numbers is generated. In this study, a novel interval was introduced, shown as (d^-, d^+) . d^- and d^+ show the intervals used to decrease and increase the values, respectively. Generating random particles in new intervals, the particle swarm optimization allows finding the optimum solution in the new interval.

4.7.1 Reforming interval of variables

During the optimization process by PSO if variable reaches the end of the interval, the interval of variables will be increased.

5. TEST PROBLEMS AND RESULTS

The GSU-PSO optimization procedure developed in this work was tested by solving three weight minimization problems of steel frames: a 1-bay 10-story, a 3-bay 15-story frames and a 3-bay 24-story frames Optimization results were compared with literature to demonstrate the validity of the proposed approach. The optimization algorithms were coded in MATLAB while structural analysis was performed using the SAP2000 code.

In this work, gridding obtained by dividing the total space into 10 divisions. Different functions by varying steps and intervals is investigated

5.1 Design of 1-bay 10-story frame

Fig. 4 shows the configuration and applied loads of 1-bay 10-story frame structure

consisting of 30 members. For this example, Pezeshk et al. [27] used GA. The same frame was also designed by Camp et al. [28] utilizing ant colony optimization (ACO), also by Degertekin [29] using Harmony search (HS), and by Kaveh and Talatahari [30] using improved ant colony optimization (IACO).

Fabrication conditions requiring the same beam section to be used for every three consecutive stories starts from the foundation. Furthermore, the same column section must be used for every two consecutive stories. The beam element groups are chosen from all 267 W-shaped sections of the AISC standard list, while the column element groups are limited to W12 and W14 sections (66 W-shapes).

The frame was designed according to the AISC-LRFD specifications and uses inter-story drift constraints: inter story drift < story height/300. The modulus of elasticity of the material E is equal to 200 GPa and the yield stress f_y is set to 248.2 MPa.

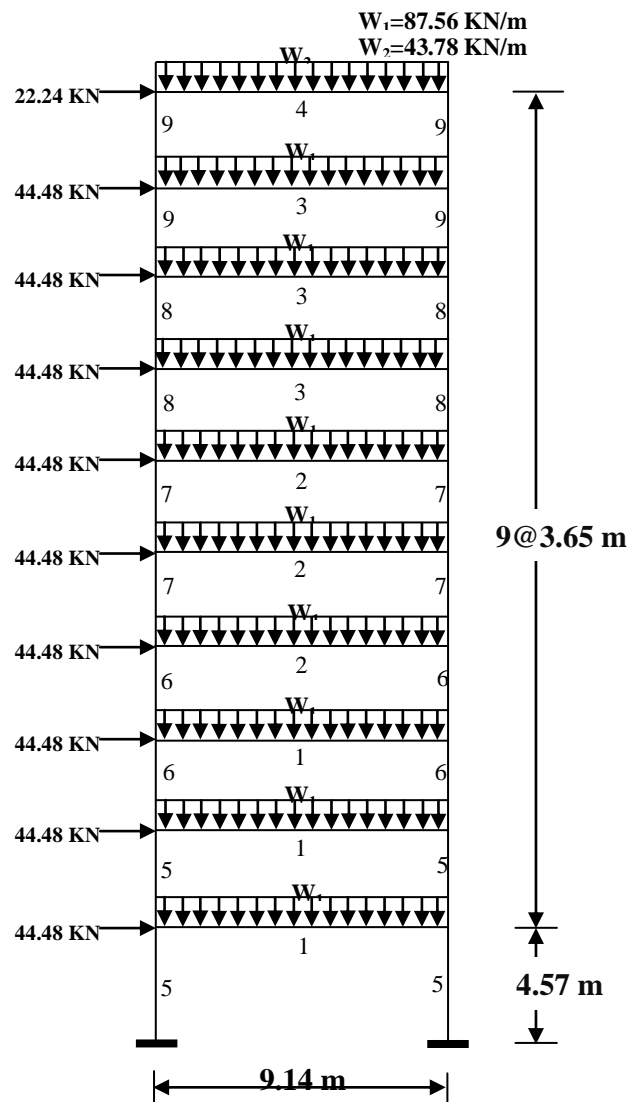


Figure 4. Schematic of the 1-bay 10-story frame and loads acting on the structure

Fig. 5 compares the best convergence histories for the GSU-PSO and PSO algorithms. the optimum design of the frame is obtained after 2800 analyses using PSO, having the minimum weight of 315.43 KN. The optimum design for GSU-PSO is computed as 287.182 KN within 1920 frame analyses. GSU-PSO algorithm with a 31% reduction in the number of analyses caused a 9 percent improvement in the optimal solution. It can be seen that the convergence speed at the beginning of the optimization process using algorithms GSU-PSO is much better than the conventional PSO.

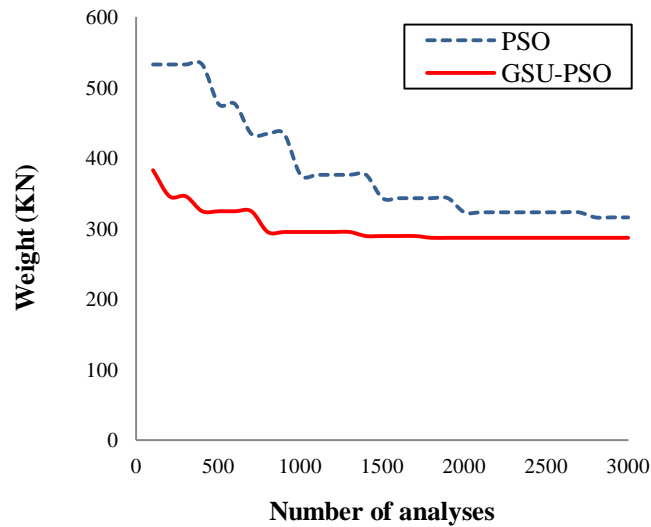


Figure 5. Comparison of the best-weight convergence curves of GSU-PSO and standard PSO obtained in the 1-bay 10-story frame problem

Table 1: Optimization results obtained for the 1-bay 10-story frame problem.

Element group no.	AISC W-shapes					
	Element group	GA ¹	ACO ²	HS ³	IACO ⁴	Present work
1	Beam 1-3S ⁵	W33x118	W30x108	W33x118	W 33x118	W33x118
2	Beam 4-6S	W30x90	W30x90	W30x99	W30x90	W30x99
3	Beam 7-9S	W27x84	W27x54	W24x76	W24x76	W27x84
4	Beam 10S	W24x55	W21x44	W18x46	W14x30	W 18x40
5	Column 1-2S	W14x233	W14x233	W14x211	W14x233	W14x233
6	Column 3-4S	W14x176	W14x176	W14x176	W14x176	W14x176
7	Column 5-6S	W14x159	W14x145	W14x145	W14x145	W14x145
8	Column 7-8S	W14x99	W14x99	W14x90	W14x90	W12x106
9	Column 9-10S	W12x79	W12x65	W14x61	W14x65	W12x65
Weight (KN)		289.72	278.48	275.18	274.99	287.182
Number of analyses		3000	8300	3690	2500	1920

1-Genetic algorithm[27]
2- Ant colony optimization[28]
3- Harmony search[29]
4-Improved ant colony optimization[30]
5-S= Story

Optimization results are compared with the literature as listed in Table 1. In order to converge to a solution in the GSU-PSO algorithm, approximately 1920 frame analyses are required, which not only is less than the 3000 analyses required by the standard GA [27], but also less than the 8300, 3690 and 2500 analyses required by ACO [28], HS [29] and IACO [30], respectively.

5.2 Design of 3-bay 15-story frame

The topology and the service loading conditions for a three-bay fifteen-story frame consisting of 105 members are shown in Fig. 6. Displacement and AISC combined strength constraints were included as optimization constraints. Similar to the previous problem, the modulus of elasticity of the material E is equal to 200 GPa and the yield stress f_y is set to 248.2 MPa. The beam and column element groups are chosen from all 267 W-shaped sections of the AISC standard list.

Fig. 7 compares the best convergence histories for the GSU-PSO and PSO algorithms. The optimum design of the frame is obtained after 5400 analyses by using PSO, having the minimum weight of 519.24 KN. The optimum design for GSU-PSO is calculated 396.749 KN within 3070 frame analyses. GSU-PSO algorithm with a 43% reduction in the number of analyses also caused a 24 percent improvement in the optimal solution. It can be seen that the convergence speed at the beginning of the optimization process is much better using algorithms GSU-PSO than that using the conventional PSO.

Optimization results are compared with the literature in Table 2. The GSU-PSO algorithm required 3070 frame analyses to converge a solution, which is significantly less than the 50000, 5800, 9900, 6000, 4050 and 3200 analyses required by PSO [31], HPSACO [31], HBB-BC [32], ICA [33], ES-DE [34] and ECBO [35], respectively. The best weight obtained by the GSU-PSO was recorded less than PSO [31], HPSACO [31], HBB-BC [32], ICA [33] and ES-DE [34].

Fig. 8 shows the inter-story drift for each story of the frame design. The stress ratio for the three-bay 15-story frame design obtained by GSU-PSO is shown in Fig. 9.

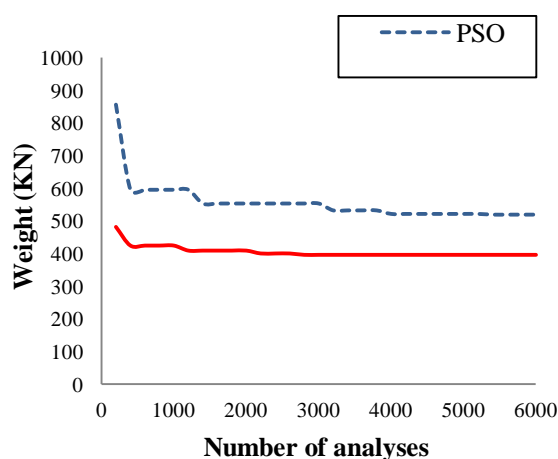


Figure 7. Comparison of the best-weight convergence curves of GSU-PSO and standard PSO obtained in the 3-bay 15-story frame problem

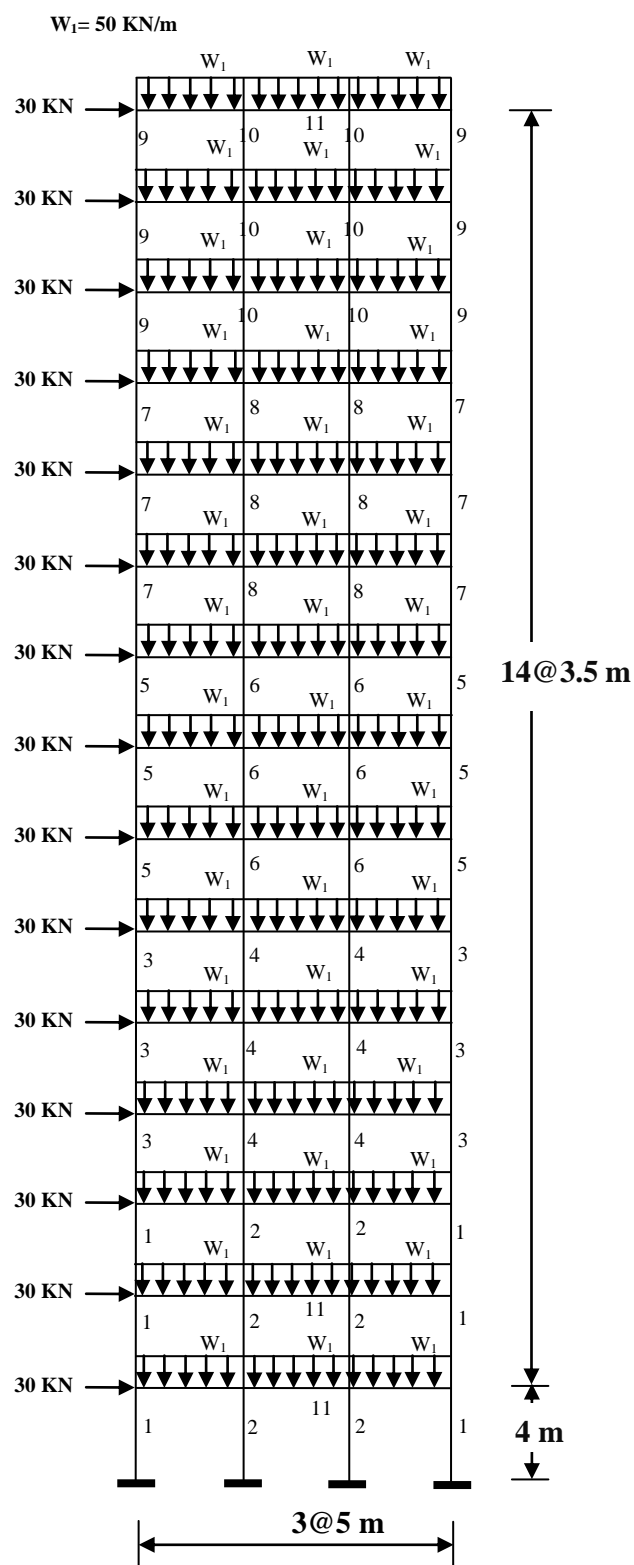


Figure 6. Schematic of the 3-bay 15-story frame and loads acting on the structure

Table 2: Optimization results obtained for the 3-bay 15-story frame problem.

Element group no.	AISC W-shapes						Present work
	PSO ¹	HPSACO ²	HBB-BC ³	ICA ⁴	ES-DE ⁵	ECBO ⁶	
1	W33 X 118	W21X 111	W24 X 117	W24 X 117	W18 X 106	W14X99	W21 X 44
2	W33 X 263	W18 X 158	W21 X 132	W21 X 147	W36 X 150	W27X161	W12 X 106
3	W24 X 76	W10 X 88	W12 X 96	W27 X 84	W12 X 79	W27X84	W27 X 161
4	W36 X 256	W30 X 116	W18 X 119	W27 X 114	W27 X 114	W24X104	W27X 84
5	W21 X 73	W21 X 83	W21 X 93	W14 X 74	W30 X 90	W14X61	W27 X 114
6	W18 X 86	W24 X 103	W18 X 97	W18 X 86	W10 X 88	W30X90	W16 X 67
7	W18 X 65	W21 X 55	W18 X 76	W12 X 96	W18 X 71	W14X48	W18 X 86
8	W21 X 68	W27 X 114	W18 X 65	W24 X 68	W18 X 65	W14X61	W24 X 55
9	W18 X 60	W10 X 33	W18 X 60	W10 X 39	W8 X 28	W14X30	W16 X 67
10	W18 X 65	W18 X 46	W10 X 39	W12 X 40	W12 X 40	W12X40	W8 X 24
11	W21 X 44	W21 X 44	W21 X 48	W21 X 44	W21 X 48	W21X44	W16 X 45
Weight (kN)	496.68	426.36	434.54	417.466	415.06	386.933	396.749
Number of analyses	50,000	6800	9900	6000	4050	3200	3070

1- particle swarm optimization [31]
 2- heuristic particle swarm ant colony optimization[31]
 3- hybrid Big Bang–Big Crunch optimization[32]
 4- imperialist competitive algorithm[33]
 5- eagle strategy algorithm with differential evolution[34]
 6-enhanced colliding bodies optimization [35]

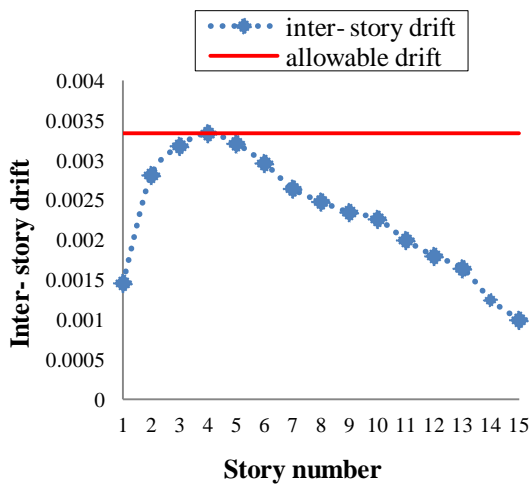


Figure 8. Inter-story drift for the 3-bay 15-story frame design

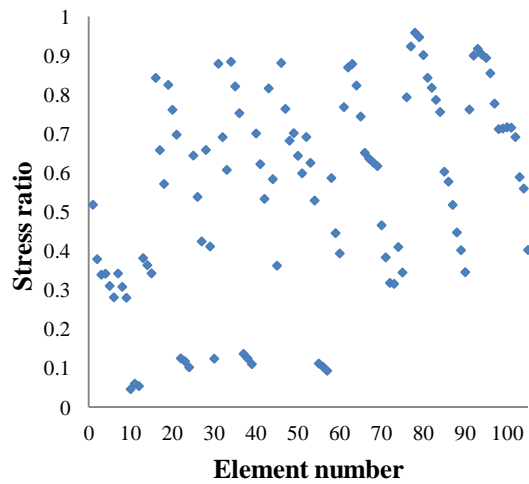


Figure 9. Stress ratios of the members for the 3-bay 15-story frame

5.2 Design of 3-bay 24-story frame

Fig. 10 shows the configuration and applied loads of 3-bay 24-story frame structure consisting of 168 members. For this example, Camp et al. [27] used ant colony

optimization (ACO). The same frame was also designed by Degertekin [28] utilizing Harmony search (HS), also by Safari [29] using modified multi-deme genetic algorithm (MMDGA), also by Mahmoud et al. [29] using enhanced harmony search (EHS) and by Kaveh et al. [30] using enhanced colliding bodies optimization (ECBO).

The frame is designed following the LRFD specification and uses an inter-story drift displacement constraint. The material properties are a modulus of elasticity equal to $E = 205$ GPa and a yield stress of f_y is set to 230.3 MPa. Fabrication conditions require the same beam section be used in the first and third bay on all floors except roof beams: therefore, there are only four groups of beams. Beginning from the foundation, the exterior columns are combined together into one group, the interior columns are combined together in another group over three consecutive stories. In summary, there are 16 groups of columns and 4 groups of beams for a total of 20 design variables. Cross-sections of beam elements can be chosen from all the 267 W-shapes while cross-sections of column elements are limited to W14 sections (37 W-shapes).

The optimum design of the frame is obtained after 11300 analyses using PSO, having the minimum weight of 997.132 KN. The optimum design for GSU-PSO is computed as 906.21 KN within 6120 frame analyses. GSU-PSO algorithm with a 46% reduction in the number of analyses caused a 9 percent improvement in the optimal solution.

Optimization results are compared with the literature in Table 3. The GSU-PSO algorithm required 6120 frame analyses to converge a solution, which is significantly less than the 15500, 14561, and 15360 analyses required by ACO [36], HS [29] and ECBO [35], respectively.

Fig. 11 shows the inter-story drift for each story of the frame design. Fig. 12 represents the stress ratios for the members of the 3-bay 24-story frame. The maximum value of the stress ratio is 82%.

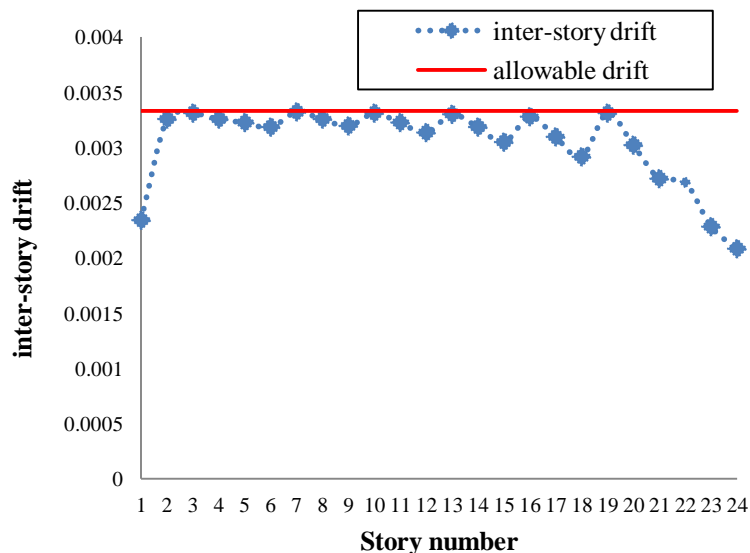


Figure 11. Inter-story drift for the 3-bay 24-story frame design

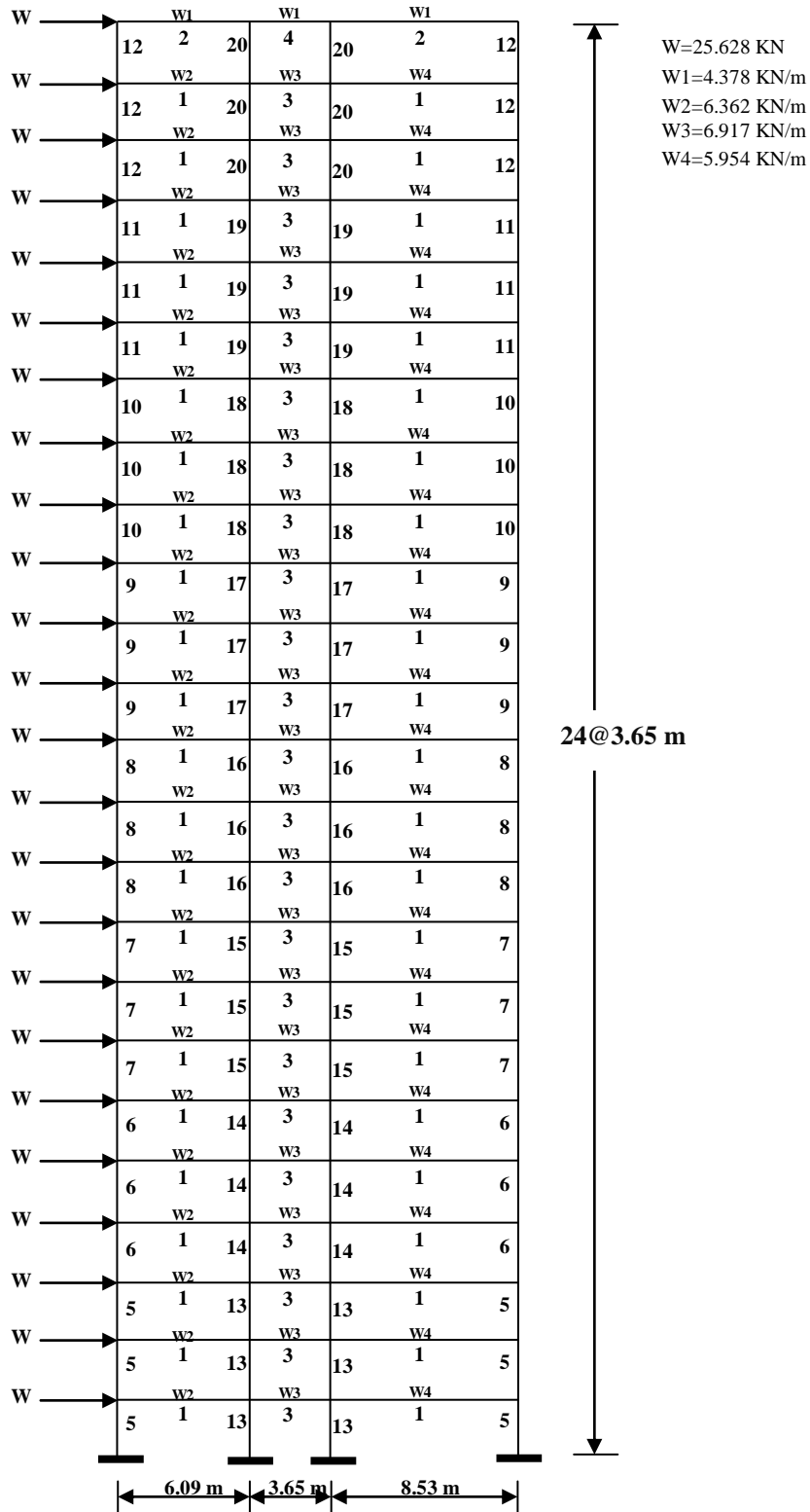


Figure 10. Schematic of the 3-bay 24-story frame and loads acting on the structure

Table 3. Optimization results obtained for the 3-bay 24-story frame problem

Element group no.	AISC W-shapes					Present work
	ACO ¹	HS ²	MMDGA ³	EHS ⁴	ECBO ⁵	
1	W30 X 90	W30 X 90	W30 X 90	W10 X 19	W30 X 90	W30X90
2	W8 X 18	W10 X 22	W8 X 15	W12 X 190	W6 X 15	W8X15
3	W24 X 55	W18 X 40	W24 X 55	W6 X 8.5	W24 X 55	W21X48
4	W8 X 21	W12 X 16	W10 X 15	W24 X 370	W6 X 8.5	W21X57
5	W14 X 145	W14 X 176	W14 X 159	W14 X 132	W14 X 145	W14X132
6	W14 X 132	W14 X 176	W14 X 132	W14 X 30	W14 X 132	W14X120
7	W14 X 132	W14 X 132	W14 X 90	W14 X 99	W14 X 99	W14X99
8	W14 X 132	W14 X 109	W14 X 90	W14 X 53	W14 X 90	W14X82
9	W14 X 68	W14 X 82	W14 X 61	W14 X 74	W14 X 74	W14X74
10	W14 X 53	W14 X 74	W14 X 48	W14 X 26	W14 X 38	W14X48
11	W14 X 43	W14 X 34	W14 X 48	W14 X 68	W14 X 38	W14X34
12	W14 X 43	W14 X 22	W14 X 22	W14 X 193	W14 X 22	W14X26
13	W14 X 145	W14 X 145	W14 X 109	W14 X 145	W14 X 99	W14X109
14	W14 X 145	W14 X 132	W14 X 99	W14 X 26	W14 X 99	W14X120
15	W14 X 120	W14 X 109	W14 X 99	W14 X 26	W14 X 99	W14X109
16	W14 X 90	W14 X 82	W14 X 74	W14 X 43	W14 X 82	W14X99
17	W14 X 90	W14 X 61	W14 X 68	W14 X 26	W14 X 68	W14X74
18	W14 X 61	W14 X 48	W14 X 53	W14 X 120	W14 X 61	W14X61
19	W14 X 30	W14 X 30	W14 X 26	W14 X 426	W14 X 30	W14X34
20	W14 X 26	W14 X 22	W14 X 22	W14 X 68	W14 X 22	W14X26
Weight (kN)	980.677	955.745	898.127	864.734	896.842	906.21
Number of analyses	15,500	14,651	4,750	1,259	15,360	6,120

1- ant colony optimization [36]
2 harmony search algorithm [29]
3- modified multi-deme genetic algorithm [37]
4- enhanced harmony search [38]
5-enhanced colliding bodies optimization [35]

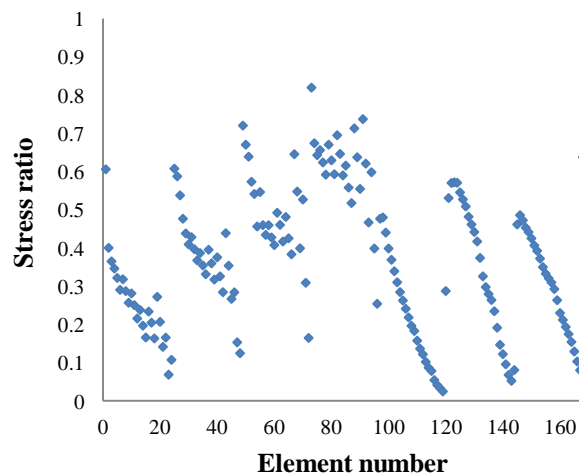


Figure 12. Stress ratios of the members for the 3-bay 24-story frame

6. CONCLUSION

PSO is a heuristic method inspired by social behavior of animals such as bird flocking or fish schooling. It is a multi-agent and randomized search technique which does not require an explicit relationship between the objective function and constraints, and it is not necessary for a given function to be derivable. Moreover, there are simple concepts, that is, few parameters to adjust. Despite all these advantages, the optimization time for solving frame structures is high.

In this paper, in order to improve the convergence speed and quality of response of the PSO algorithm, the implementation of an efficient hybrid algorithm based on particle swarm optimization, grid search method and univariate method (GSU-PSO) is introduced. In this method, at phase 1, by applying the grid search method the whole search space is divided into a series of grids. The objective function is calculated with random-generated particles. By using a method derived from the univariate method the variables of the best particle are allowed to modify their values in a stepwise manner. At phase 2, particle swarm optimization found the optimum solution by considering an interval close to the variables and generating random particles in new intervals.

The GSU-PSO method was tested on several steel frames from the literature. Major advancements of GSU-PSO explored in the present study may highlight the fact that, it is always fair to search for still better techniques to improve the results and yet not to claim that global optimum reached. The proposed technique, that introduces a hybrid method terminated by PSO, showed that the number of structural analyses for optimization could still be significantly reduced compared to other results reported in the literature while slightly modify the optimum solution. The technique could especially be recommended in some of the problems where there is no limit in the search space. It could even then narrow itself to the most required search space at the beginning of the procedure before optimization search takes place. The proposed technique by no means is a break through, but a search for better results without violating the constraints, could always be fruitfully challenging.

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