Scientia Iranica A (2013) 20(4), 1124–1132

Sharif University of Technology
Scientia Iranica
Transactions A: Civil Engineering
www.scientiairanica.com

Stochastic directional search: An efficient heuristic for structural optimization of building frames

M. Shahrouzi* and M. Pashaei

Department of Engineering, Kharazmi University, Tehran, Iran

Received 1 March 2012; received in revised form 28 September 2012; accepted 21 April 2013

KEYWORDS
Stochastic directional search;
Structural design;
Sizing optimization;
Building frame.

Abstract. Performance of an optimization heuristic highly depends on the method it employs to represent and decompose the search space. A class of optimization methods, including swarm intelligence, utilizes a special way of decomposing the search space via specified direction states. The present work expands the idea, providing a stochastic directional state search with tuned thresholds for selecting every direction state. The proposed meta-heuristic is then utilized for the problem of structural weight minimization in building frames under lateral and gravitational loading using a finite element analyzer. Treating a number of examples from the literature, the efficiency and effectiveness of the proposed method are shown to be superior to some other meta-heuristics, including an improved particle swarm optimizer.

1. Introduction

Structural optimization is a class of problems dealing with numerous design variables, confined due to a variety of code-specific constraints. As a benchmark problem, discrete sizing optimization has been addressed by many investigators up to date.

The search space of structural optimization is usually discrete and non-convex, with a narrow feasible region, due to many limiting constraints. Hence, efficient and diverse approaches are required in this field. The class of traditional mathematical programming, MP [1], used to be applied to this field, providing a rapid local search, but its gradient-based nature is not suited to discrete spaces. Additionally, the performance of MP algorithms highly depends on the assumption of the initial starting point. Meta-heuristic algorithms, on the other hand, are more generalized and suitable for such discrete problems compared to MP techniques. They can provide effective solutions in the neighbourhood of the global optimum, via practical time, by extensive sampling of the design space, with no need for gradient information. Consequently, meta-heuristic applications have received considerable attention in the field of optimal structural design during recent decades [2,3]. Some of the interesting classes include evolutionary and genetic algorithms [4], ant colony optimization [5], harmony search [6], particle swarm optimization [7-10], big bang-big crunch [11], charged system search [12], colonial competition [13] and firefly algorithm [14].

Every meta-heuristic uses its special way of representing the search space, and aims to provide proper balance between intensification and diversification. Genetic algorithms alter coded genotypes resulting in diverse jumps in the phenotype space. Ant colony agents move through vertices on characteristic graphs of the discrete problem. Particle swarm optimization, PSO, uses vector-sum representation and a movement strategy among the search space, which has been shown to be effective in many engineering design problems [8-10].

The present work utilizes such a decomposition of search space in a different manner to provide an

*. *Corresponding author. E-mail address: shahruzi@khu.ac.ir*

efficient algorithm called Stochastic Directional Search, SDS. Its basics are first reviewed in the following sections. Then, it is utilized for structural design problem formulation and applied to a number of examples for sizing building frame members. The effectiveness and efficiency of SDS is finally compared with PSO via discussion on the results of the treated examples.

2. Basic components of pabticle swarm optimization

Swarm intelligence is assigned to a class of algorithms inspired by bird flocks or fish schools, providing a smart social behavior by the group action of simple individual agents. Simulation of such an action for numerical problems was introduced as particle swarm optimization by Kennedy and Eberhart in 1995 [7]. Since then, several variants of PSO have been successfully applied to engineering optimization problems [15-20].

Any particle movement in PSO is analogous to the variation of a current design vector to another. Such a design variation is performed via summation of three vectors, each one oriented towards a direction term denoted as a state [21]. The first vector directs in the same way as the previous movement and is thus called the inertia term. The second, called the cognitive term, models a simple memory for each particle to move towards its best experienced position up to the current iteration. The third one is a social term, directed toward the global best-so-far solution already found by the entire swarm. The standard PSO is thus formulated by the following relations:

$$\underline{X}_i^{k+1} = \underline{X}_i^k + \underline{V}_i^{k+1}, \tag{1}$$

$$\underline{V}_i^{k+1} = c_1 \underline{V}_i^k + rc_2(\underline{P}_i^k - \underline{X}_i^k) + rc_3(\underline{B}^k - \underline{X}_i^k). \tag{2}$$

For the artificial unit time interval, the velocity term, $\underline{V}_i^{+1}k$, in Eq. (1), denotes how the position of the ith particle (the corresponding design vector) is changed, moving into new position, $\underline{X}_i^{k+1}$, in the next iteration, $k+1$. The velocity, $\underline{V}_i^{k+1}$, in every next step is a vector-sum of the 3 terms in Eq. (2). $\underline{B}^k$ is the global best position found by the entire swarm, while $\underline{P}_i^k$ denotes the best position of every ith particle up to now. r is a uniformly random scalar between -1 and 1.

In an improved PSO variant, Eq. (2) is modified, adding the direction of a randomly generated design vector, $\underline{R}_i^k$, as the 4th term in the following relation:

$$\underline{V}_i^{k+1} = c_1 \underline{V}_i^k + rc_2(\underline{P}_i^k - \underline{X}_i^k) + rc_3(\underline{B}^k - \underline{X}_i^k) + rc_4(\underline{R}_i^k - \underline{X}_i^k). \tag{3}$$

In Eqs. (2) and (3), c_1, c_2, c_3 and c_4 stand for the inertial, cognitive, social and random vector coefficients that confine movement size towards the corresponding directions during any iteration of the algorithm.

3. The proposed stochastic directional search

In an iteration of PSO, the velocity of a particle is not necessarily parallel to any of the terms in Eq. (3), but is a vector sum of such randomly scaled vectors.

Here, a new algorithm is proposed, called the Stochastic Directional Search, SDS. According to SDS strategy, a move-step in any search iteration is oriented towards only one of the candidate states, i.e. inertial, cognitive, social or random directions, as depicted in Figure 1. The final path of every particle will be the vector-sum of such terms, but in consequent iterations. As a result, SDS allows explicit tuning of the probability threshold of any such state, in order to provide the desired balance between diversification and intensification by the algorithm. A roulette wheel procedure is employed for such a probability-based state selection.

4. Structural problem formulation

In order to reduce constructional cost, total structural weight is minimized under regulations of the Load and Resistant Factor Design method, due to the AISC-LRFD code [22]. The optimization problem is thus formulated, regarding the strength and serviceability constraints, as:

Minimize

$$\mathrm{W}^t = \rho.\sum_{i=1}^{M} A_i.L_i. \tag{4}$$

Subject to:

$$\left|\frac{\theta^k}{\theta^{all}}\right| - 1 \le 0, \tag{5}$$

$$\left|\frac{d_i}{d_i^{all}}\right| - 1 \le 0, \tag{6}$$

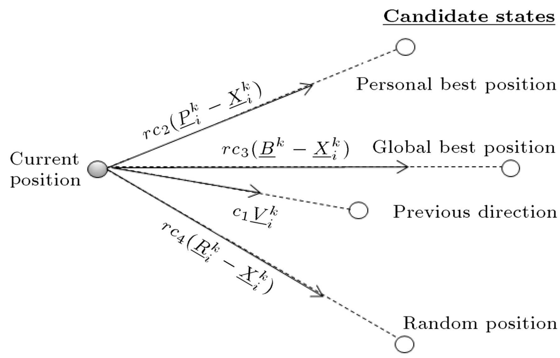

Figure 1. Candidate states for the ith particle in directional search and a sample movement vector.

$$\left|\frac{P_u}{\varphi_c P_n}\right|_i + \left|s\frac{M_u}{\varphi_b M_n}\right|_i - 1 \leq 0, \tag{7}$$

$$s = \begin{cases} \frac{8}{9} & \text{if} \quad \left|\frac{P_u}{\varphi_c P_n}\right| > 0.2 \\ 1 & \text{otherwize} \end{cases}, \tag{8}$$

$$\frac{h_c^{k+1,i}}{h_c^{k,i}} - 1 \leq 0, \tag{9}$$

$$\frac{b_g^{k,i}}{b_c^{k,i}} - 1 \leq 0, \tag{10}$$

for : $i = 1, ..., \text{number of elements}$,

$j = 1, ..., \text{number of DOFs}$,

$k = 1, ..., \text{number of stories}$,

where ρ stands for the material density, L_i and A_i denote length and cross-sectional area of the ith member, so that W^t is the total structural weight. θ^k stands for the kth story drift divided by its height, and θ^{all} denotes the corresponding allowable drift ratio. b_c^k and h_c^k are the width and height of the column's W-section in the kth story, respectively, where b_g^k denotes the corresponding girder flange width. P_u and P_n are the applied column axial force and its nominal capacity, and φ_c is the corresponding resistant factor. Similarly, M_u stands for the applied moment, while M_n and φ_b denote the nominal flexural strength and its resistant factor of the ith member, respectively.

A fly-back strategy is applied for the last two constraints. For the others, a penalty function [23] is employed using the following relation:

$$Fitness = -\text{W} \times (1 + K_p * \sum_l C_l)^\beta, \tag{11}$$

where C_l is the positive violation of the lth constraint and is taken 0 for non-violated constraints. K_p denotes the corresponding penalty factor and β is a prescribed amplifying coefficient.

5. Numerical examples

Three benchmark examples are selected from the literature [24-30] in order to evaluate performance of the proposed method. The AISC W-section list is considered as the discrete set for sizing the steel frame elements. In all the optimization examples, 30 particles are employed, with coefficients c_2, c_3 and c_4 taken as 2, where c_1 is linearly decreased from 0.9 to 0.4. In this study, the values of K_p and β are taken to be 1 and 3, respectively.

For the sake of true comparison, the initial randomly generated population of particles by the PSO algorithm is saved in the memory and identically used as the initial population of the SDS algorithm. Consequently, final fitness improvements are comparable between the algorithms as a measure of effectiveness. The probability thresholds are tuned after a number of trial runs as 2, 43, 54 and 1 percent for the inertial, cognitive, social and random direction states, respectively.

5.1. Ten-story one-bay frame

The 10-story frame in this example consists of 9 symmetric member groups under gravitational and lateral loading, as depicted in Figure 2 [30]. A list of W12 and W14, including 66 standard sections, are considered assignable to the columns, meanwhile all 267 standard W-sections can be chosen for the girders. Therefore, the search space cardinality in this example is $267^5 \times 66^5$; that is of order 10^{21}.

Maximum displacement (which occurs at the roof level) is restricted to 4.9 in, and allowable inter-story drift is 0.6 in for the 1st story and 0.48 in for the others.

The elastic modulus and yielding strength of constructional steel are taken as 29000 ksi and 36 ksi,

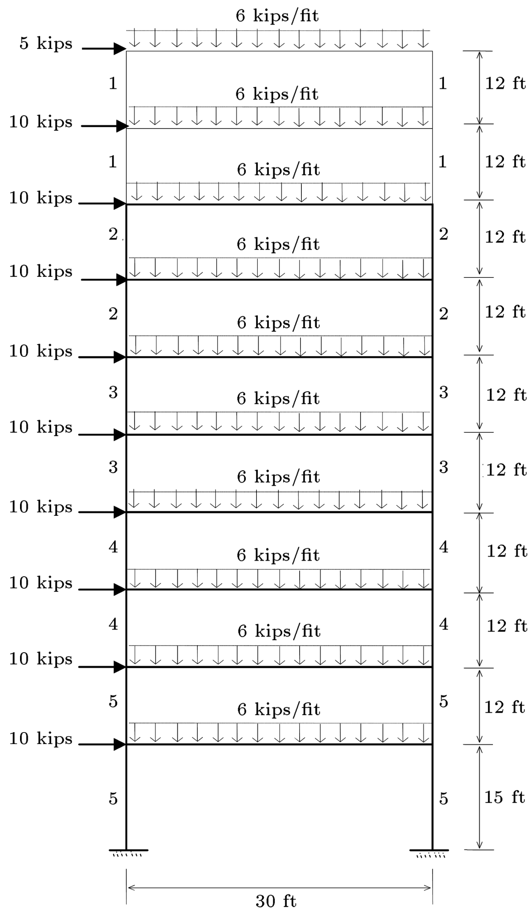

Figure 2. One-bay ten-story frame, member groups and the appllied loading.

Table 1. Comparison of optimal results by different methods for the 1-bay 10-story frame.

Element group	Optimal cross-sections						
	GA Pezeshk et al. [24]	**ACO** Camp et al. [26]	**HS** Degertekin [25]	**IACO** Kaveh and Talatahari [27]	**TALBO** Togan [28]	**PSO** Present work	**SDS** Present work
1	W14×233	W14×233	W14×211	W14×233	W14×233	W14×176	W14×159
2	W14×176	W14×176	W14×176	W14×176	W14×176	W12×170	W14×120
3	W14×159	W14×145	W14×145	W14×145	W14×145	W12×106	W14×120
4	W14×99	W14×99	W14×90	W14×90	W14×99	W12×87	W14×90
5	W12×79	W12×65	W14×61	W12×65	W12×65	W12×58	W12×58
6	W33×118	W30×108	W33×118	W33×118	W30×108	W36×150	W40×149
7	W30×90	W30×90	W30×99	W30×90	W30×90	W36×170	W33×118
8	W27×84	W27×84	W24×76	W24×76	W27×84	W24×94	W27×84
9	W24×55	W21×44	W18×46	W14×30	W21×44	W21×93	W21×44
Weight (lb)	65136	62610	61864	61820	61813	69762	60120

respectively. The effective length factors of a frame member, from typical nodes A to B, are taken to be 1 for out-of-plane motion and computed according to the following relations [31] for the in-plane motion of the frame:

$$k=\sqrt{\frac{1.6G_AG_B+4(G_A+G_B)+7.5}{G_A+G_B}}, \tag{12}$$

$$G=\frac{\sum\frac{EI_c}{l_c}}{\sum\frac{EI_g}{l_g}}, \tag{13}$$

where I_c, I_g are moment of inertia for the column and girder connected to the joint (A or B) and l_c, l_g are the corresponding member unbraced lengths, respectively. The unbraced length of any girder is taken as 1/5 of its total length.

The global best fitness achieved up to any iteration is saved and announced as the elitist fitness. The fitness history of such elitist solutions among all the search iterations is thus plotted in Figure 3 for both PSO and SDS. It is declared that, starting from the same initial point, the SDS results stand higher than the PSO. Additionally, SDS has more rapid convergence to the best solution than PSO. As declared in this example, the elitist fitness of PSO has remained constant for a number of final iterations, so it has become trapped in the local optima. In order to verify the SDS capability in over-passing local optima, it has been compared to the best results reported in the literature. According to Table 1, SDS can obtain the best structural weight of 60120 lb better than the least reported weight 61813 lb among PSO, Genetic Algorithm [24], Harmony Search [25], Ant Colony Optimization [26], Improved ACO [27] and Teaching And Learning Based Optimization, TALBO [28] belonging to the last method. In addition, Figure 4 shows that

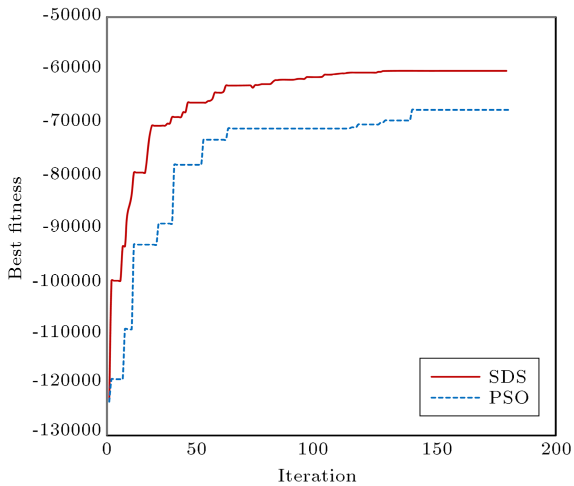

Figure 3. Convergence history of the one-bay ten-story frame.

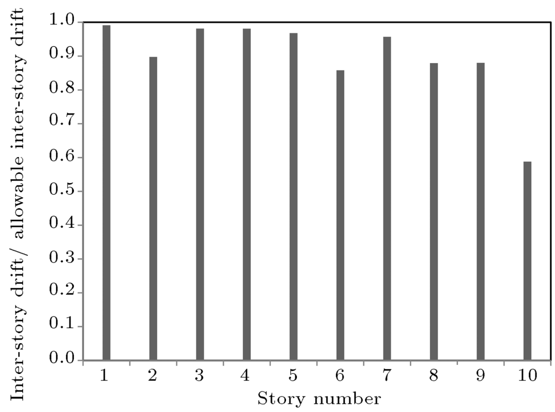

Figure 4. The optimal inter-story drift ratios obtained by SDS for the 1st example.

the proposed SDS has forced most of the inter-story drifts to get close to their allowable limit in the optimal result.

5.2. Fifteen-story three-bay frame

All standard W sections are considered as the section list in this example. The frame members are categorized in 12 groups; the first 2 belonging to the girders while the others are assigned to the column members as shown in Figure 5.

Allowable inter-story drift is confined to 0.52 in for the 1st story and 0.48 in for the others, while the maximum allowable absolute displacement of nodes at roof level is taken 6.95 in. Other assumptions, including material elastic modulus and strength, and effective and unbraced member lengths, are the same as the previous example.

In this example, the discrete search space cardinality or the number of searchable particle positions will be 267^{12}, i.e. of order 10^{29}, which is quite large. However, it is greater than the 1-bay 10-story frame. The convergence curve of Figure 6 again declares the superiority of the proposed SDS over PSO. It is notable

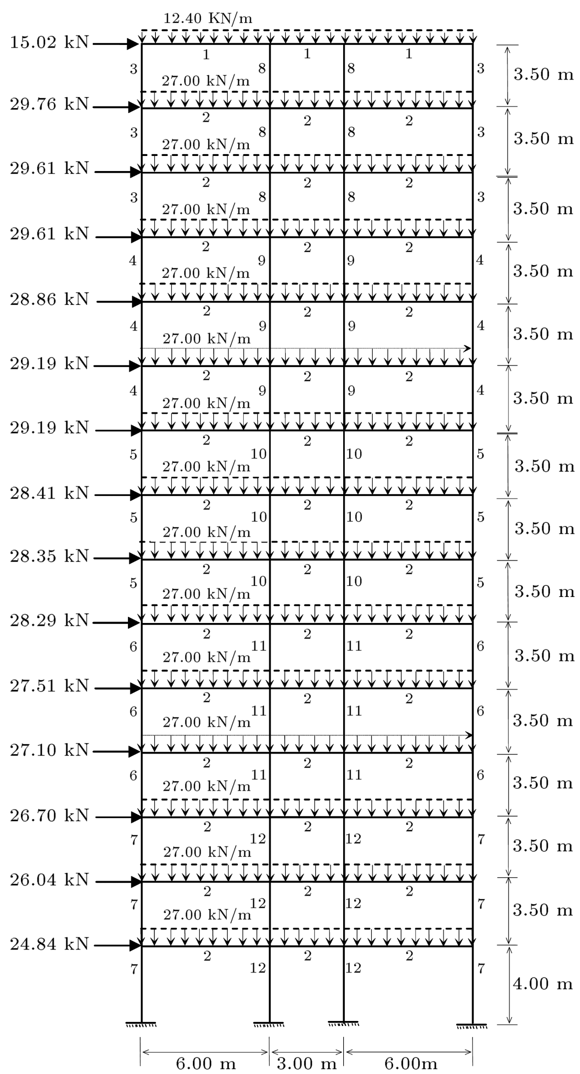

Figure 5. Three-bay fifteen-story frame, member groups and the appllied loading.

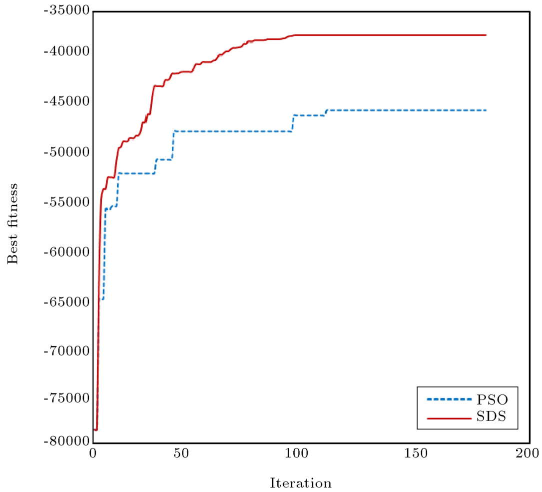

Figure 6. Convergence history of the 3-bay 15-story frame.

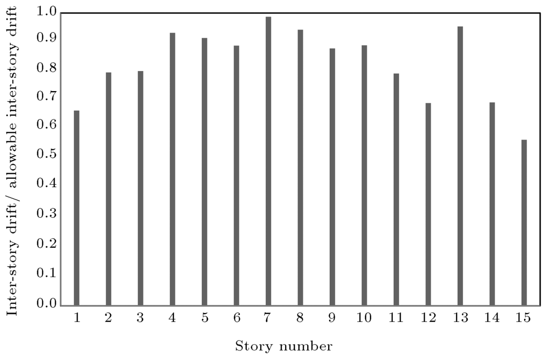

Figure 7. The optimal inter-story drift ratios obtained by SDS for the 2nd example.

that the SDS curve is also smoother than that of the PSO, which means more stable convergence toward the global optimum. The matter is confirmed by adding the previously reported best results of Genetic Algorithm and Simulated Annealing to a comparison with the present work of PSO and SDS. It is observed in Table 2 that the best structural weight of 37143 kg belongs to the proposed SDS, standing better than SA, GA [29] and PSO. In the SDS optimal solution, the inter-story drifts have gotten close to their limit, but have not overridden it. This achievement confirms the proper constraint handling capability of the algorithm (Figure 7).

5.3. Twenty-four-story three-bay frame

This example consists of a 3-bay 24-story moment frame under lateral point loads of $w = 5761.8^{\mathrm{lb}}$ at each story level, and distributed gravitational loads of $w_1 = 300^{\mathrm{lb/ft}}$, $w_2 = 436^{\mathrm{lb/ft}}$, $w_3 = 474^{\mathrm{lb/ft}}$ and $w_4 = 408^{\mathrm{lb/ft}}$, as depicted in Figure 8. Modulus of elasticity is 29732 ksi and the yielding strength of the material is assumed to be 33.4 ksi. The frame is designed under AISC-LRFD requirements, with maximum allowable

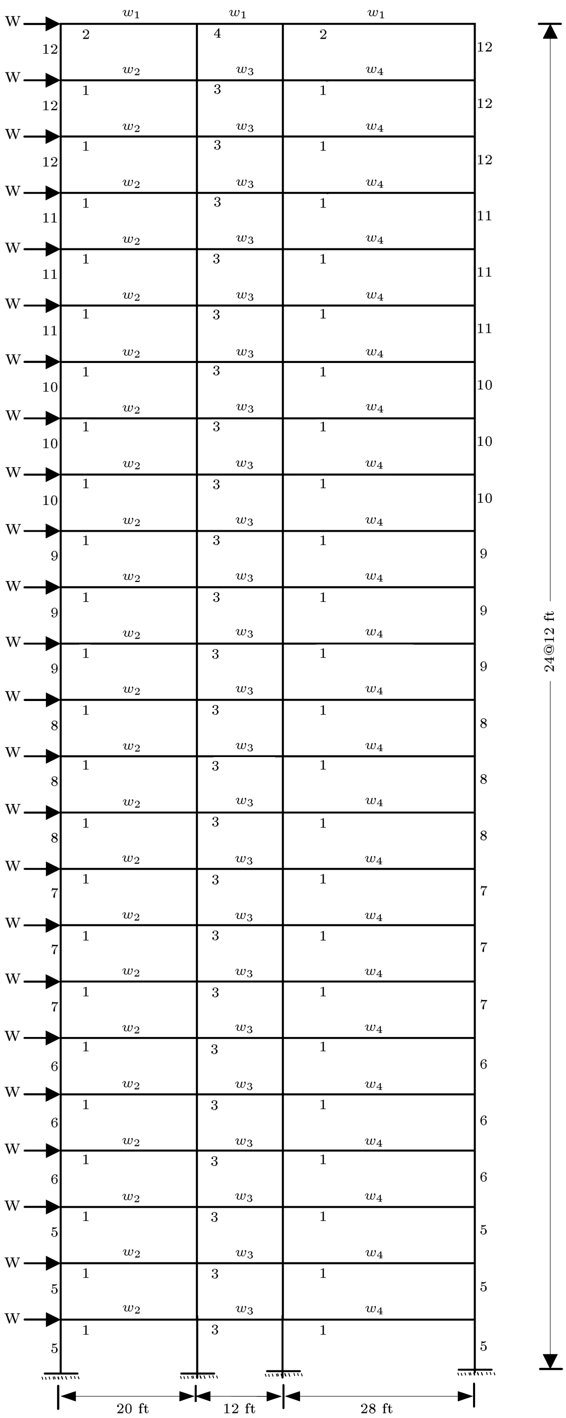

Figure 8. Applied loading and member groups for the three-bay tweny four-story frame.

displacement of 11.52 in, and inter-story drifts are confined to 0.48 in. The unbraced lengths are assigned joint-to-joint free lengths for both column and beam members. The effective length factors are computed as in the first example.

This frame consists of 96 columns in 16 groups and 72 girders in 4 groups. Considering 37 W14 sections assignable to the columns and all W-sections

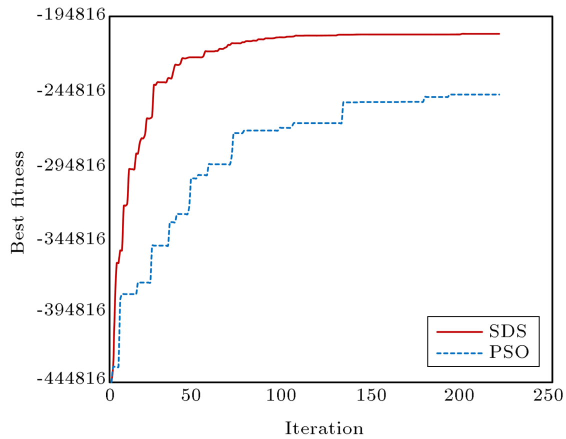

Figure 9. Convergence history of the 3-bay 24-story frame.

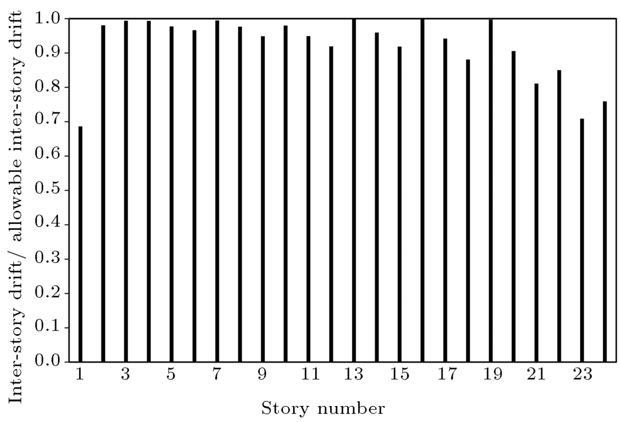

Figure 10. Maximum inter-story drift ratios for optimum design in the 3-bay 24-story frame.

to the girders, the resulting search space will be of order 10^{34}. Figure 9 shows that, even in such a large search space, the proposed algorithm is again more efficient and effective than PSO. Table 3 declares the least frame weight is obtained by SDS as 20216 lb, while it is 24868 lb for PSO. Using even more fitness evaluations by other methods, such as 13924 analyses by HS, has not revealed better results than the SDS result, which is achieved only via 6000 fitness evaluations. The matter shows the efficiency of the proposed method in addition to its effectiveness in searching the global optimum of the problem. Figure 10 also illustrates that in this higher story example, more inter-story drift responses have tended towards their constraint boundary.

6. Conclusion

In this study, directional decomposition of the search space in swarm algorithms has been concerned. Consequently, the idea of the stochastic explicit selection of direction states is utilized in the proposed SDS method. Despite vector-sum movements in any PSO

Table 2. Comparison of optimal results by different methods for the 3-bay 15-story frame.

Element group	Optimal cross-sections			
	Saka [29]		Present work	
	GA	SA	PSO	SDS
1	W21×50	W21×50	W8×67	W6×20
2	W24×55	W21×57	W24×62	W24×62
3	W10×39	W10×33	W8×67	W8×31
4	W14×53	W10×39	W10×49	W10×33
5	W14×53	W12×53	W10×27	W10×45
6	14W×68	W16×67	W10×88	W10×54
7	W24×117	W24×104	W12×87	W12×72
8	W14×43	W10×39	W8×67	W8×31
9	W14×48	W14×48	W10×54	W14×43
10	W14×68	W14×61	W12×65	W18×60
11	W14×109	W14×99	W12×120	W18×76
12	W16×100	W14×99	W18×97	W21×101
Weight (kg)	40949	39262	45240	37143

Table 3. Comparison of optimal results by different methods for the 3-bay 24-story frame.

Elements Group	Optimal cross-sections					
	ACO Camp et al. [26]	IACO Kaveh et al. [27]	HS Degertekin [25]	TALBO Togan [28]	Present works	
					PSO	PDS
1	W30×90	W30×99	W30×90	W30×90	W27×94	W30×90
2	W8×18	W16×26	W10×22	W8×18	W10×45	W8×18
3	W24×55	W18×35	W18×40	W24×62	W18×46	W21×44
4	W8×21	W14×22	W12×16	W6×9	W6×9	W6×9
5	W14×145	W14×145	W14×176	W14×132	W14×176	W14×159
6	W14×132	W14×132	W14×176	W14×120	W14×283	W14×132
7	W14×132	W14×120	W14×132	W14×99	W14×233	W14×132
8	W14×132	W14×109	W14×109	W14×82	W14×176	W14×90
9	W14×68	W14×48	W14×82	W14×74	W14×38	W14×61
10	W14×53	W14×48	W14×74	W14×53	W14×109	W14×48
11	W14×43	W14×34	W14×34	W14×34	W14×38	W14×26
12	W14×43	W14×30	W14×22	W14×22	W14×53	W14×22
13	W14×145	W14×159	W14×145	W14×109	W14×145	W14×99
14	W14×145	W14×120	W14×132	W14×99	W14×109	W14×109
15	W14×90	W14×99	W14×82	W14×90	W14×120	W14×90
16	W14×90	W14×99	W14×82	W14×90	W14×120	W14×90
17	W14×90	W14×82	W14×61	W14×68	W14×90	W14×74
18	W14×61	W14×53	W14×48	W14×53	W14×22	W14×53
19	W14×30	W14×38	W14×30	W14×34	W14×26	W14×38
20	W14×26	W14×26	W14×22	W14×22	W14×38	W14×22
Weight (lb)	220465	217464	214860	203008	242868	202116
Num. of required Analyses	15500		13924		6000	6000

iteration, the SDS strategy enables application of a roulette wheel selection, guided by fine tuned probability thresholds, in selecting each direction state. Hence, SDS is expected to show a superior performance by finer balancing the intensification and diversification features of the search process.

Such an expected search improvement is then evaluated using three literature benchmarks of steel moment frames. PSO results in the examples proves it can lead to premature convergence into local optima, while the smoother convergence curves of SDS exhibit its effectiveness and higher stability search toward the global optimum.

The achieved solutions by PSO and SDS in the treated examples were further compared with those reported in literature by GA, ACO, SA, HS and TALBO algorithms.

Consequently, SDS led to the highest quality solutions among all these algorithms, even with less computational effort in function evaluations. It again confirmed the importance of the better tuning capabilities in SDS.

It is worth mentioning that in the optimal frame design by SDS, inter-story drifts tend to their allowable limits, showing the proper constraint handling performance of this algorithm.

Finally, in view of the obtained results, the developed stochastic directional search is an effective and efficient search method in weight minimization of moment frames under behavioral and section-size constraints. Based on the revealed theoretical discussion, further investigation into the performance of the algorithms in other fields of optimization is recommended as a future scope of research.

References

1. Topping, B.H.V. "Mathematical programming techniques for shape optimization of skeletal structures", *Shape and Layout Optimization of Structural System and Optimality Criteria Methods*, Rozvany GIN (Ed.). Springer, Vienna (1992).
2. Ghasemi, M.R., Hinton, E. and Wood, R.D. "Optimization of trusses using genetic algorithms for discrete and continuous variables", *Eng. Computations*, **3**, pp. 272-301 (1999).
3. Deb, K. and Gulati, S. "Design of truss-structures for minimum weight using genetic algorithms", *Finite Elements in Analysis and Design*, **37**, pp. 447-465 (2001).
4. Holland, J.H., *Adaptation in Natural and Artificial Systems*, University of Michigan (1975).
5. Dorigo, M.A., Colorni, A. and Maniezzo, V. "The ant system: Optimization by a colony of cooperating agents", *IEEE Trans. Sys. Man Cybernetics*, **26**(1) (1996).
6. Geem, Z.W., Kim, J.H. and Loganathan, G.V. "A new heuristic optimization algorithm: Harmony search", *Simulation*, **76**(2), pp. 60-68 (2001).
7. Kennedy, J. and Eberhart, R. "Particle swarm optimization", *Proc. Int. Conf. Neural Networks*, Perth, Australia, pp. 1942-1948 (1995).
8. Kennedy, J. and Eberhart, R., *Swarm Intelligence*, Academic Press, London (2001).
9. He, S., Wu, K.H., Yen, J.Y., Sanders, J.R, and Paton, R.C. "A particle swarm optimizer with passive congregation", *Bio Systems*, **78**, pp. 135-147 (2004).
10. Sedlaczek, K. and Eberhard, P. "Optimization of nonlinear mechanical systems under constraints with the particle swarm method", *Proc. of Applied Mathematics and Mechanics*, **4**(1), pp. 169-170 (2004).
11. Osman, K. Erol and Ibrahim, E. "A new optimization method: Big Bang-Big Crunch", *Advances in Eng. Software,* **37**(2), pp. 106-111 (2006).
12. Kaveh, A. and Talatahari, S. "A novel heuristic optimization method: Charged system search", *Acta Mechanica*, **213**, pp. 267-289 (2010).
13. Atashpaz-Gargari, E., Hashemzadeh, F., Rajabioun, R. and Lucas, C. "Colonial competitive algorithm: A novel approach for PID controller design in MIMO distillation column process", *Int. J. of Intelligent Computing and Cybernetics*, **1**(3), pp. 337-355 (2008).
14. Yang, X.S. "Firefly algorithms for multimodal optimization", in Watanabe O, Zeugmann T, Editors. *Stochastic Algorithms: Foundations and Applications, SAGA 2009, Lecture Notes in Computer Science, 5792*, Berlin: Springer-Verlag, pp. 169-178 (2009).
15. Fan, S.K., Liang, Y.C. and Zahara, E. "Hybrid simplex search and particle swarm optimization for the global optimization of multimodal functions", *Eng. Optimization*, **36**, pp. 401-418 (2004).
16. Li, L., Wang, L. and Liu, L.H. "An effective hybrid PSOSA strategy for optimization and its application to parameter estimation", *Applied Mathematics and Computation*, **179**, pp. 135-146 (2006).
17. He, Q. and Wang, L. "An effective co-evolutionary particle swarm optimization for constrained engineering design problems", *Eng. Applications of Artificial Intelligence*, **20**, pp. 89-99 (2007).
18. Kao, Y.T. and Zahara, E. "A hybrid genetic algorithm and particle swarm optimization for multimodal functions", *Applied Soft Computing,* **8**, pp. 849-857 (2008).
19. Kaveh, A. and Talatahari, S. "Particle swarm optimizer, ant colony strategy and harmony search scheme hybridized for optimization of truss structures", *Computers and Structures*, **87**(5-6), pp. 267-283 (2009).
20. Kaveh, A. and Talatahari, S. "Hybrid charged system search and particle swarm optimization for engineering design problems", *Eng. Computations*, **28**(4), pp. 423-440 (2011).
21. Shahrouzi, M. "Pseudo-random directional search: A new heuristic for optimization", *Int. J. of Optimization in Civil Eng.*, **1**(2), pp. 341-355 (2011).

22. American Institute of Steel Construction, *Manual of Steel Construction Load & Resistance Factor Design*, 3rd Ed., Chicago: AISC (2001).

23. Joghataei, A. and Takalloozadeh, M. "Improving penalty functions for structural optimization", *Scientia Iranica, Transactions A: Civil Eng.*, **16**(4), pp. 308-320 (2009).

24. Pezeshk, S., Camp, C.V. and Chen, D. "Design of nonlinear framed structures using genetic algorithms", *Structural Eng.*, **126**(3), pp. 382-388 (2000).

25. Degertekin, S.O. "Optimum design of steel frames using harmony search algorithm", *Structural and Multidisciplinary Optimization*, **36**, pp. 393-401 (2008).

26. Camp, C.V., Bichon, B.J. and Stovall, S.P. "Design of steel frames using ant colony optimization", *Structural Eng.*, **131**(3), pp. 369-379 (2005).

27. Kaveh, A. and Talatahari, S. "An improved ant colony optimization of planar steel frames", *Eng. Structures*, **32**, pp. 864-873 (2010).

28. Togan, V. "Design of planar steel frames using teaching-learning based optimization", *Eng. Structures*, **34**, pp. 225-232 (2012).

29. Saka, M.P. "Optimum design of steel frames using stochastic search techniques based on natural phenomena: A review in: Topping BHV", *Computing in Civil Eng. Tools and Techniques,* Saxe-Coburgh Publications pp. 105-147 (2007).

30. Dogan, E. and Saka, M.P. "Optimum design of unbraced steel frames to LRFD-AISC using particles warm optimization", *Advances in Eng. Software*, **46**(1), pp. 27-34 (2012).

31. Dumonteil, P. "Simple equations for effective length factors", *Eng. J., AISE*, **29**(3), pp. 111-115 (1992).

Biographies

Mohsen Shahrouzi was born in 1975. He obtained his BS degree in Civil Engineering and his MS degree in Earthquake Engineering from Sharif University of Technology, in 1997 and 2000, respectively, and, subsequently, received his PhD degree from the International Institute of Earthquake Engineering and Seismology, in 2006. Dr. Shahrouzi is currently Assistant Professor of Earthquake Engineering at Kharazmi University, Iran. He is author of 50 papers, 17 of which have been published in international journals and 7 presented at international conferences.

Mahdi Pashaei was born in 1982. He obtained his BS degree in Agricultural Engineering from the Islamic Azad University of Torbat-e Heydariyeh, Iran, in 2006, and his MS degree from the Engineering Department of Kharazmi University, Tehran, Iran, in 2012. His research interests include meta-heuristic optimization and structural design under dynamic loading.