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A NEW MEMETIC SWARM OPTIMIZATION FOR SPECTRAL LAYOUT DESIGN OF BRACED FRAMES

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ABSTRACT

For most practical purposes, true topology optimization of a braced frame should be synchronized with its sizing. An integrated layout optimization is formulated here to simultaneously account for both member sizing and bracings' topology in such a problem. Code-specific seismic design spectrum is applied to unify the earthquake excitation. The problem is solved for minimal structural weight under codified stress, deformation and also user-defined weak-storey and architectural constraints. Particle swarm optimization is hybridized with an extra memory consideration strategy to solve this problem. As another issue, Baldwin effect of memetic algorithm is utilized in the proposed method to enhance its search capability regarding the geometrical and topological constraints. Treating a number of planar braced frames revealed superior performance of the proposed hybrid method partiqularly in avoiding premature convergence over the common particle swarm optimiztion for such a discrete problem.

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KEY WORDS: Baldwin effect; memetic algorithm; swarm intelligence; layout optimization; spectral seismic design; steel braced frame.

1. INTRODUCTION

Bracing members are common tools to control lateral sways of the building frames under seismic or wind loadings. Their application is necessary in tall buildings where the moment frame itself cannot confine the lateral displacements and drifts in their appropriate limits [1]. Spatial topology of bracings can help in such cases as a more effective lateral force resistant system. However, many practical and architectural requirements tend to minimize the number or positioning of bracings among the structural frames. Therefore, a trade-off

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problem arises to find the best design of a braced frame with minimal weight but sufficient structural strength [2].

In this field, continuum approaches seek the best material distribution in a medium and derive conceptual designs to be further interpreted to practical ones [3, 4]. However, discrete approaches search for the optimal placement of distinct members in a skeletal framework [5, 6]. Traditional deterministic methods generate an initial space of potential members called structural universe or ground structure and gradually removing inefficient members out of this feasible space to achieve the optimal design [5, 7-8]. More recent approaches use stochastic methods including meta-heuristics in order to better search for global optima in such discrete design spaces [6, 9-13].

The present work proposes a hybrid particle swarm and memetic algorithm to solve this problem accounting for architectural constraints as well as structural drift and stress limits. It takes benefit of both directional search in swarm intelligence and exploitation feature of evolutionary computation [11-14]. An efficient encoding of the design variables is thus utilized to simultaneously deal with both bracings' topology and frame sizing variables in order to seek true optimum. Performance of the proposed method is compared with standard particle swarm intelligence in a number of building frame examples to reveal its superior capability in escaping local optima toward higher quality results with acceptable stability of convergence.

2. DYNAMIC EQUIATION OF MOTION AND SPECTRAL DESIGN

A braced frame can be modelled with structural Multi-Degree of Freedom, MDF system. The corresponding mass, stiffness and damping properties are introduced by $\underline{m}$, $\underline{k}$ and $\underline{c}$ matrices, respectively. Concerning horizontal ground acceleration time-history $a_g(t)$ as the seismic excitation source, governing equations of motion are given by:

$$\underline{m}\,\ddot{\underline{u}} + \underline{c}\,\dot{\underline{u}} + \underline{k}\,\underline{u} = -a_g\,\underline{m}\underline{1} \tag{1}$$

With the assumption of classical damping, the above system of equations can be decoupled by modal decomposition as:

$$\underline{M}\,\ddot{\underline{z}} + \underline{C}\,\dot{\underline{z}} + \underline{K}\,\underline{z} = -a_g\,\underline{\Phi}^T\,\underline{m}\underline{1}\ , \quad \underline{u} = \underline{\Phi}\,\underline{z} \tag{2}$$

Where modal mass, stiffness and damping are introduced by the following diagonal matrices, respectively:

$$\underline{M} = \underline{\Phi}^T\,\underline{m}\underline{\Phi}\ ,\ \underline{K} = \underline{\Phi}^T\,\underline{k}\underline{\Phi}\ ,\ \underline{C} = \underline{\Phi}^T\,\underline{c}\underline{\Phi} \tag{3}$$

No surprise that solution of such a MDF system depends on the input excitation. An alternative way is to apply spectral design to reduce such a dependency on the input record in estimating maximal design responses. The excitation source is thus a unified design spectrum given by the desired code of practice for given soil condition, peak ground acceleration and seimicity of the construction site [15].

Since concentrated mass model is employed in the present work, corresponding rotational degrees of freedom are condensed to the translational ones. For any complete model of bracings' topology and sized structural members, the required stress and deformation responses and constraints are derived using modal analysis under combined gravitaional and spectral seimic loadings.

3. PROBLEM FORMULATION

The optimization problem is to minimize the structural weight for the assigned frame sections providing that all the addressing stress/displacement limitations of the design code are satisfied.

$$\begin{aligned}
&\textit{Minimize} && W(\underline{X}) = \rho \sum_{i=1}^{NumMembers} A_i L_i \\
&\textit{Subject to} && g_i(\underline{X}): \sum_{direction=1}^{2} \frac{\sigma_{i,direction}}{\sigma^{allowable}} - 1 \le 0,\; i = 1,2,\ldots, NumMembers \\
& && g_s(\underline{X}): \frac{drift_s}{drift^{allowable}} - 1 \le 0,\; s = 1,2,\ldots, NumStories \\
& && g_{ws}(\underline{X}): \frac{NumUnbracedStories}{NumStories} - 1 \le 0 \\
& && g_c(\underline{X}): \frac{NumBracedPanels}{TotalNumPanels} - \frac{\beta}{100} \le 0
\end{aligned} \tag{4}$$

According to the employed *direct index coding* [16], each design variable, x_i may be assigned an integer index from 0 or 1 to maximal number of available sections for the corresponding member group. The zero indices are implied only for bracings that are being omitted during layout optimization. Such an encoding leads to minimal chromosome length and is much superior to traditional binary/topological strings [17]. The stress and deformation constraints in Eq.4 are due to regulations of *Iranian code of seismic design*, ICPSRDB 2800-05, and AISC-ASD89 steel design code [18]. An extra constraint, g_{wc}, is applied to avoid occurrence of weak stories during the search. It is based on the fact that braced panel has much more stiffness than a pure moment frame panel against lateral sway. According to the architectural constraint, g_c, no more than β percent of frame openings are allowed to be braced.

In this study the allowable stress design requirements due to AISC-ASD89 and ICPSRDB 2800-05 are employed. The following penalty function is used to evaluate equivalent fitness function.

$$Fitness = -f(x_1,\ldots,x_m) * (1 + \sum_l r_p C_l) \tag{5}$$

in which *f* stands for the objective function (weight), C_l denotes the l^{th} constraint violation and r_p is the employed penalty coefficient. The section indices assigned to the *m* member groups are denoted by $\underline{X} = < x_1, ..., x_m >$ as the structural design vector.

4. BALDWIN EFFECT IN MEMETIC ALGORITHMS

Memetic Algorithm, MA, as a generalized kind of Evolutionary Computing, EC, is systematically introduced by Moscato's [19]. MA's include an embedded problem-specific learning operator which frequently is applied to population in evolutionary search. An individual is called a meme when experiencing such learning during its life-time prior to fitness evaluation. Thus, MA's combine both generality of EC frameworks and problem-specifity of local search operators.

There are two distinct approaches in learning strategy of memetic algorithms; namely Lamarckian evolution and Baldwin effect [20-22]. In the first approach, chromosome itself is being changed during learning mechanism and its fitness is evaluated afterwards. In contrary, Baldwinian approach does not return the experienced changes during a meme learning process to its corresponding chromosome in the population but only associates it the new fitness after meme evolution. In another word, the method of fitness evaluation is altered by undergoing some type of problem-specific exploitation or local search rather than implementing new fitness function.

In order to indirectly apply the geometric constraint, section indices in the design vector are sorted in descending order before fitness evaluation; that is to insure no column section in any lower storey is lighter than the upper storey column. Additionally, the architectural constraint, g_c, is strictly satisfied before fitness evaluation by gradual omission of less stressed bracing members in similar groups up to acheive the sparse enough bracing layout.

5. HYBRID MEMETIC AND PARTICLE SWARM OPTIMIZER

Swarm intelligence inspired by social behaviour of natural swarms like bird's flocking or ant colonies is a base of many current meta-heuristic algorithms [11, 23-24]. In this category, *particle swarm optimization*, PSO, is considered here to be further hybridized with memetic features in stochastic search. According to the standard PSO, a particle as the search agent, gradually improves its location as a candidate design vector X, iteratively due to the following relations:

$$\underline{V}_i^{k+1} = c_i \underline{V}_i^k + r.c_c(\underline{X}_i^{Pbest,k} - \underline{X}_i^k) + r.c_s(\underline{X}_{Gbest}^k - \underline{X}_i^k) \quad (6)$$

$$\underline{X}_i^{k+1} = \underline{X}_i^k + \underline{V}_i^{k+1} \quad (7)$$

Where $\underline{V}_i^{k+1}$ counts for the designed change in the current design vector $\underline{X}_i^k$ to be applied at the next iteration *k*+1, to the i^{th} particle. Meanwhile c_i, c_c, c_s stand for inertial, cognitive and social factors and r is output of a random generator function which uniformly lies between -1 and 1. $\underline{X}_i^{Pbest,k}$ denotes the best pervious position experienced by the i^{th} particle while

$\underline{X}^{k}_{Gbest}$ accounts for the fittest of such vectors in the current iteration. The former mimics the cognitive and the latter models social behaviour of swarm particles in searching for the global optimum.

The proposed hybrid algorithm, however, substitutes the Eq.6 with the following relation:

$$\underline{V}_i^{k+1} = c_i \underline{V}_i^k + r.c_c(\underline{X}_i^{Pbest,k} - \underline{X}_i^k) + r.c_s(\underline{X}^k_{Gbest} - \underline{X}_i^k) + r.c_{cr}(\underline{X}^k_{Cr} - \underline{X}_i^k) \quad (8)$$

In which the additional term directs toward $\underline{X}^k_{Cr}$ where the maximal step size is controlled by the fixed parameter c_{cr}. The newcomer vector $\underline{X}^k_{Cr}$ is derived exploiting the population of particles by the following subroutine:

1. Initiate an empty auxiliary population with at most the same size of the swarm.
2. Randomly select two particles out of the current swarm as the parents
3. Perform a two-point crossover over the selected parents to obtain two children
4. Let every child (as a meme) experience the individual learning / growth
5. Evaluate the fitness values for the grown children
6. Select the fitter of them and add it to the auxiliary population.
7. Repeat the above steps from step (2) until the auxiliary population is filled
8. Identify $\underline{X}^k_{Cr}$ as the fittest individual in the recently generated auxiliary population

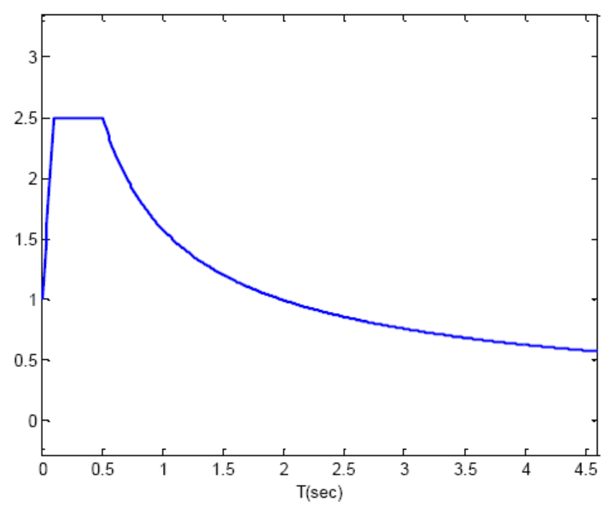


Figure 1. The employed spectral response amplification factor due to ICPSRDB 2800-05

6. NUMERICAL EXAMPLES

Performance of the proposed hybrid method, EPSO, is compared with a non-exploited PSO treating some examples of planar steel frames. Typical storey height and bay length are 3.30 and 5.00 meters, respectively. Note that all connects are rigid in this study.

Dead load, qD, of 9810 N/m is exerted on each beam in the floors meanwhile applying live load, qL, of 4905 N/m on them. The design spectrum of ICPSRDB 2800-05, by PGA of 0.3g, soil type II and R factor of 7 for a residential building is taken as the seismic spectral loading; qE. The behavioral constraints are then evaluated under the following combinations of aforementioned loading states:

$$qD \tag{9}$$

$$qD+qL \tag{10}$$

$$0.75(qD \pm qE) \tag{11}$$

$$0.75(qD+qL \pm qE) \tag{12}$$

Spectral responses are scaled so that the resulting base shear is normalized with that offered by the seismic design code. Tuning parameters is a main challenge for application of meta-heuristics [25]. In the present study, each example is run for a number of trials to finalize algorithms' parameters and then repeated to obtain statistical results. Table 1 gives typical control parameters used for PSO and EPSO in the present study. The inertial coefficient is linearly decreased from 0.8 to 0.4 in order to insure better exploration as the search progress.

Table 1: The employed control parameters for optimization

Method	*PopSize*	*NumIters*	c_i	c_c	c_s	c_{cr}
PSO	10	300	0.8~0.4	1	1	-
EPSO	10	300	0.8~0.4	1	1	0.5

6.1 The 8-storey 7-bay frame

In this example, columns in every 2 stories are symmetrically grouped as shown in Fig. 2 and the same is done for beams grouping. Grouping of knee bracings is however performed only to deserve symmetry and being changed between story levels (Fig. 3). All structural members are made of St-37 steel with elasticity modulus of $2\times10^{10}\,Kgf/m^2$ and yield stress of $2.4\times10^{7}\,Kgf/m^2$. There are 221 standard AISC sections available for beams/columns; from $W10\times49$ to $W40\times294$.The bracings' section list include $W4\times13$ to $W14\times257$ in addition to a null-section for simultaneous topology optimization. That means a search space of the order of 10^{185} which is considerably great. The architectural constraint in this example implies that no more than 29% of the frame openings be braced.

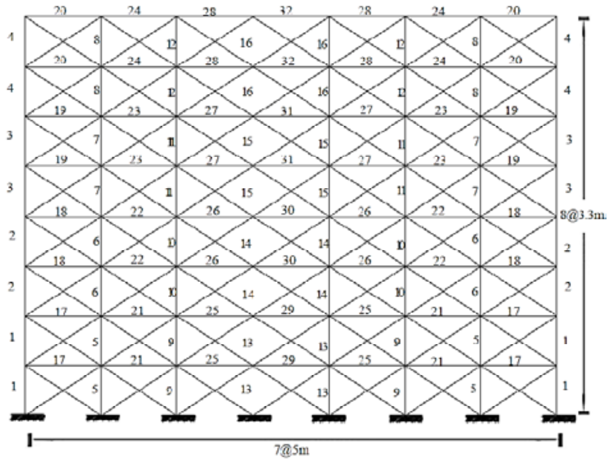


Figure 2. Dimensions and member grouping for beams/columns in the 1st example

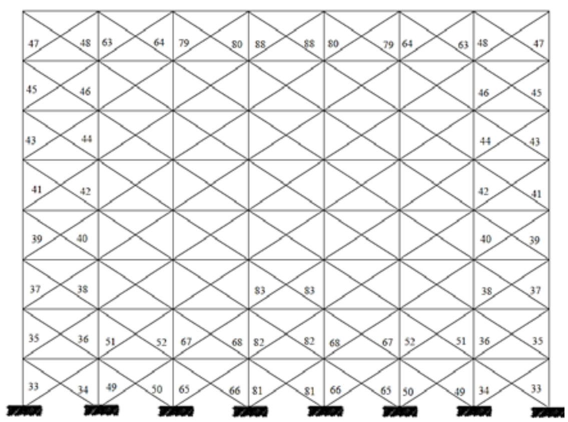


Figure 3. Member grouping for bracings in the 1st example

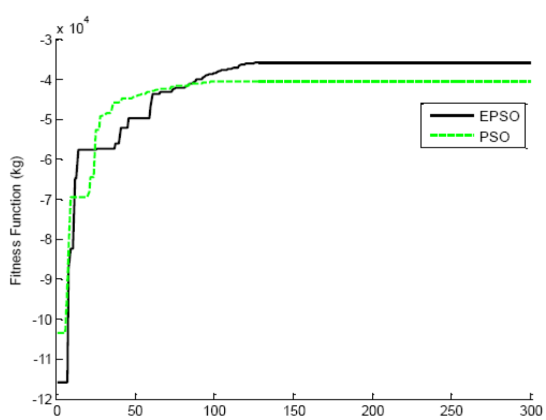


Figure 4. Comparison of EPSO convergence vs. PSO in spectral design of the 1st example

According to the statistics of this 8 storey example in Table 2, the proposed EPSO has achieved higher quality results in the best, mean and also the worst case; that is, 12% to 37% optimal weight improvement in different cases. Such a superior effectiveness can also be observed in the convergence history of the best run in Fig. 4. In This result may be addressed by enhanced refinement because of added extra local search capability to the algorithm in the proposed EPSO. However, the figure also shows some delay in obtaining the final higher quality result by the present work. In another word, the efficiency of PSO in this example is greater in the charge of being trapped in the local optimum in comparison with EPSO.

The final bracing layouts in Fig. 5 reveal that both methods have strictly satisfied the panel covering constraint, however, the proposed EPSO has performed it with fewer number of bracing diagonals.

Table 2: Statistical results of braced frame layout optimization in the first example

Method	Best weight (kg)	Mean weight (kg)	Worst weight (kg)	Standard Deviation
PSO	40619	55499	79163	11618
EPSO	35926	43291	49543	5120

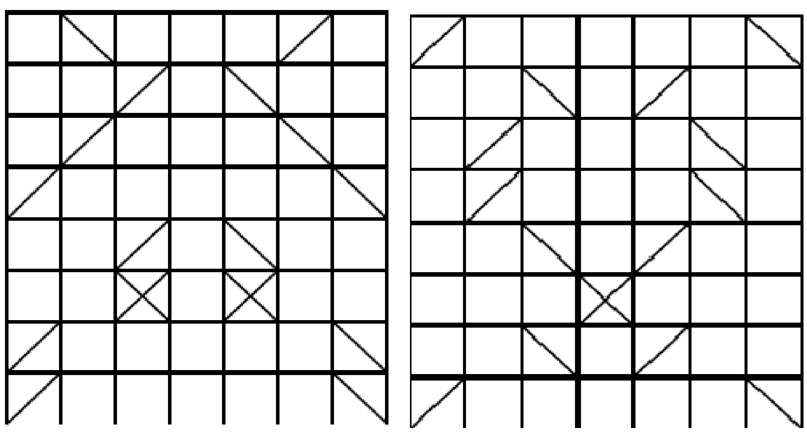


Figure 5. The best achieved braced frame layouts by (a) PSO and (b) EPSO in the 1st example

6.2 The 15-storey 4-bay frame

Here, member grouping is applied by the same rule as the previous example resulting in 40 beam/column and 100 bracing groups, respectively. There are 240 standard AISC $W\,10\times 49$ to $W\,44\times 355$ sections made of steel material grade St-37 for beams/columns and 94 sections from $W\,4\times 13$ to $W\,14\times 257$ with an additional null-section for bracings' optimization. The covering constraint of braced panels is taken $\beta = 50\%$ in this example.

Table 3: Statistical results of braced frame layout optimization in the second example

Method	Best weight (kg)	Mean weight (kg)	Worst weight (kg)	Standard Deviation
PSO	54252	77243	99832	14600
EPSO	46883	62045	78187	10423

Considering sample result of Fig. 6, it can be realized that EPSO can escape from local optima toward higher quality solution while PSO has led to premature convergence. The trend of such auxiliary sudden fitness jumps gets smoother as the search progresses. Such a higher effectiveness of EPSO with respect to PSO is confirmed by Table 3, showing 14, 20 and 22% optimal weight improvement for the best, mean and the worst cases, respectively. In addition, less standard deviation of final results during several independent runs again confirms superior stability of the proposed algorithm over PSO. Comparing final achieved layouts of the two algorithms, it seems that EPSO can lead to more uniform layouts in such moment frame examples.

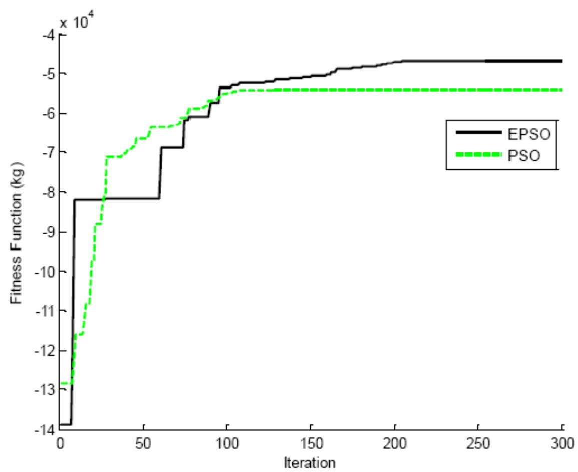
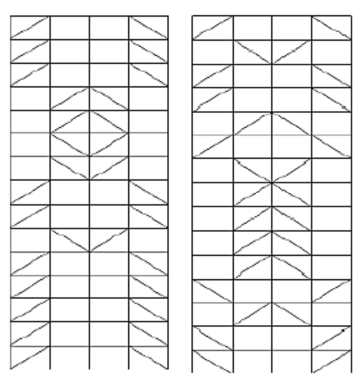


Figure 6. Comparison of EPSO convergence vs. PSO in spectral design of the 2nd example



(a)

Figure 7. The best achieved braced frame layouts by (a) PSO and (b) EPSO in the 2nd example

6.3 The 15-storey 7-bay frame

Applying the same rule as previous examples, 32 beam, 32 column and 169 bracing groups are generated for this 15-storey 7-bay frame. Here, 240 standard AISC sections made of St-37 steel; i.e, $W\,10\times49$ to $W\,44\times355$ for beams/columns and 114 sections from $W\,4\times13$ to $W\,16\times77$ are used for bracings. The covering constraint of braced panels is taken $\beta = 29\%$. More number of iterations is employed to search such a great design space in this example.

Fig. 8 compares convergence of the best runs. The previous observations in superior effectiveness of EPSO has stood stable in this example, however, requiring more sever fitness jumps to escape from premature convergence, in spite of PSO. Statistical report of Table 4 confirms the matter as the minimal weight improvement in different cases varies between 11% to 20%. In this example with greater search space, the standard deviation of EPSO is about half the PSO, showing its superiority in stability of the final optimal designs.

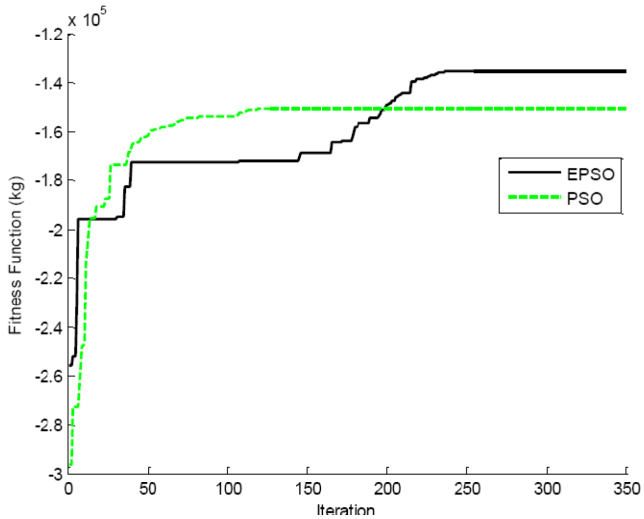


Figure 8. Comparison of EPSO convergence vs. PSO in spectral design of the 3rd example

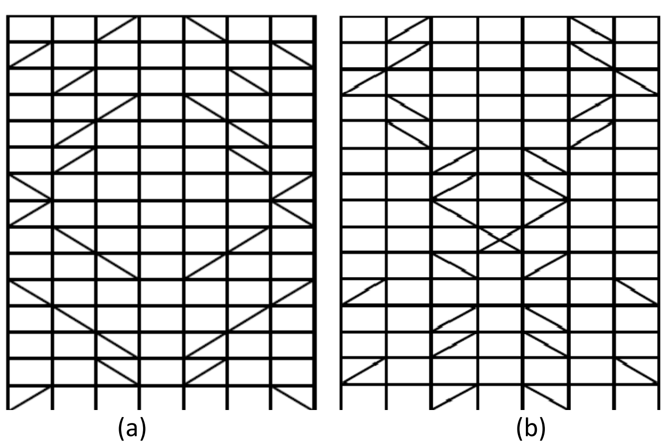


Figure 9. The best achieved braced frame layouts by (a) PSO and (b) EPSO in the 3rd example

Table 4: Statistical results of braced frame layout optimization in the third example

Method	Best weight (10^3 kg)	Mean weight (10^3 kg)	Worst weight (10^3 kg)	Standard Deviation
PSO	151	174	203	18.2
EPSO	135	148	163	8.9

Furthermore, concerning Fig. 8 it is declared that EPSO has not only achieved a more uniform solution but also has satisfied the architectural constraint with less number of braced panels in the frame.

7. CONCLUSION

In this paper a new hybrid method is proposed for simultaneous topology and size optimization of braced frames under spectral seismic and static gravitational loading. Since the design variables are discrete indices, the swarm memory is exploited as a first learning strategy. The second one, however, is a problem-specific meme evolution. In this regard Baldwin approach is utilized in order not to exert uncontrolled changes in the current individuals' memory during the search, but only evaluate the fitness of each meme in a new manner. That is sorting the column indices in each vertical grid together with eliminating extra braces up to desired covering ratio among the frame panels. The first satisfies geometric constraint of no upper storey column section be heavier than its lower one, while the second satisfies architectural constraint. A strategy to avoid weak/unbraced stories is also applied during such meme evolution.

The proposed hybrid memetic and swarm optimization is then applied to some examples of low- and medium-rise braced frames with different aspect ratios. The results show strict satisfaction of the aforementioned constraints in addition to the penalized behavioral limits on combined stress and drift ratios due to the design code requirements. Applying spectral seismic design by dynamic modal analyses provided more accurate distribution of responses than most previous studies in literature. These utilized features show desirability of the proposed method from practical point of view.

Further comparison of EPSO performance with the PSO declared superior effectiveness of the proposed method in capturing higher quality results in all the treated examples. That is achieving improvement of optimal structural weights from 11% to 37% in a variety of statistical tests. Study of resultant elite fitness histories declared that PSO has more rapid convergence than EPSO in charge of leading to premature convergence. In contrary, the proposed EPSO could over pass such local optima toward higher fitness by less deviation of final designs during several independent runs. It led to more uniform topology of final braced panels among the treated frames than PSO. The results also declared superior local search capability of EPSO with respect to PSO particularly in satisfying practical covering constraint using less number of bracing diagonals.

In the light of the achieved results, EPSO can provide proper balance between exploration and local search refinement taking benefit of global search in PSO as well as problem-specific learning of memetic approaches. Hence, the present study offers it as an effective method of braced frame layout optimization considering both practical and technical points of view.

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