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Steel Frame Optimal Design Using MHBMO Algorithm

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Abstract

Various deterministic and stochastic algorithms have been used as optimization tools in different engineering problems over the last decade. In this regard, the Modified Honey Bee Mating Optimization (MHBMO) algorithm may be considered as a typical swarm-based approach for optimizing numerous problems in engineering fields. In this paper, a design procedure based on the MHBMO technique was developed for discrete optimization of frames consisting W-shapes. The objective function in this research is to obtain the minimum weight of frames subjected to both strength and displacement requirements imposed by the American Institute for Steel Construction (AISC) and Load Resistance Factor Design (LRFD). Several frame examples from the literature were examined to verify not only the suitability of the design procedure but also the robustness of the MHBMO algorithm for frame structure design. The optimum results obtained by the MHBMO algorithm performs the best in comparison with other available techniques in the literature for all three steel frames. In conclusion, the results shows that the MHBMO algorithm is a powerful and applicable optimization method for design of frames consisting W-shapes.

Keywords: design of steel frames, the MHBMO algorithm, optimization

1. Introduction

Optimization can be defined as the process of problem solving in which it is necessary to maximize or minimize a function within a domain. The objective function, which may contain several variables, may be restricted to some constraints. Although many different sets of variables of the search domain might satisfy the described restrictions, the optimum solution to the problem is the one minimizing (or maximizing) the associated mathematical function.

In the optimum structural design methods, one of the main goals is to reduce the total weight of the structure by decreasing the weight of the material necessary for construction. This goal can be obtained by minimizing the size of the structural elements considering their load carrying capacity. In this regard, the methods seeking for the global optimum under the constraints by considering discrete design variables become popular among the researchers and the engineers (Li *et al.*, 2009; Rahami *et al.*, 2008). Despite of various optimization methods, which were utilized for optimizing structures, several innovative search-based techniques inspired from nature were applied forsolving complicated engineering problems. In these techniques, the natural phenomena such as survival of the fittest, the social interaction of ant colonies, swarm intelligence, the process of food foraging of honey bees, etc. are simulated by a numerical algorithm (Karaboga, 2005; Geem *et al.*, 2001). These methods are very suitable and effective in finding the solution of discrete structural optimization problems (Toğan and Daloğlu, 2008; Walls and Elvin, 2010; Barbosa *et al.*, 2008; Sonmez, 2011).

Recently, Abbass (2001a,b) developed an optimization algorithm based on the honey-bee mating process. He showed that this algorithm has a great potential and good perspective for the solution of various optimization problems. The Honey Bee Mating Optimization (HBMO) algorithm has also remarkable accuracy and calculation speed to deal with the optimization problems. Honey-bee mating may be considered as a typical swarm-based optimization approach. The description and the advantages of the HBMO algorithm are presented in detail in Refs. (Afshar *et al.*, 2007; Page, 1980; Niazkar and Afzali, 2015a; Niazkar and Afzali, 2015b). Although this optimization technique was successfully utilized for solving many civil engineering problems in the literature (Esmi Jahromi and Afzali, 2014; Niazkar and Afzali, 2015a; Niazkar and Afzali, 2015b; Afzali, 2016a; 2016b), it did not applied for optimum design of steel structures.

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In this paper, a design procedure employing the Modified Honey Bee Mating Optimization (MHBMO) technique is introduced for discrete optimization of planar steel-frames weight. First, the MHBMO algorithm is introduced and the simulation steps in this algorithm are presented. Afterwards, the formulation of the optimum design problem is illustrated. In this section, minimizing the total weight of the frame structure(s) subjected to the constraints in the form of strength and displacement requirements imposed by the American Institute for Steel Construction (AISC) and Load Resistance Factor Design (LRFD), is considered as the objective function. Three frame examples from the literature are examined to verify the suitability of the mentioned design procedure. Finally, the obtained results with the MHBMO algorithm is the best ones for the examples in comparison to the result of other techniques.

2. Principals of the Original HBMO Method

The Honey Bee Mating Optimization (HBMO) algorithm, which inspired by social behavior of bees, consists of a single queen, from zero to several thousand drones, usually 10,000 to 60,000 workers and broods (Afshar *et al.*, 2007). The HBMO algorithm simulates the mating process of honey bees, which is actually the mating process of the queen of the hive (Niknam *et al.*, 2011). At the beginning of the algorithm, a queen starts the mating flight. Then, the drones follow her and try to mate with her in the air. In a typical mating-flight, each queen mates with the several drones. In each mating, the sperm reaches the spermatheca and accumulates there to form the genetic pool of the colony (Nourani *et al.*, 2008). The drones, fathers of colony, practically considered as agents that pass one of their mother's gametes and function to enable females to act genetically as males. Worker bees specialized in brood care (Horng and Jiang, 2011). At the beginning of the algorithm, the user must define a number corresponding to the queen's size of spermatheca matrix which corresponds to the maximum number of the queen's mating in a single mating flight. Each time the queen successfully mates with a drone the genotype of the drone is stored in the queen's spermatheca matrix and a variable is increased by one until the size of spermatheca is reached. Another two parameters must be defined too, the number of queens and the number of broods that will be borne by all queens.

In this implementation of Honey Bees Mating Optimization (HBMO) algorithm, the number of queens is set equal to one and the number of broods is set equal to the size of queen's spermatheca matrix. Then the mating flight of the queen begins. At the start of the queen's flight, the queen is initialized with her maximum energy (the speed and the energy of the queen are randomly generated) and returns to her nest when her energy is less than a threshold value and the spermatheca is not full (Marinakis *et al.*, 2011). In order to develop the algorithm, the capability of workers is restrained in brood care and thus each worker may be regarded as a heuristic that acts to improve and/or take care of a set of broods. At the start of a mating flight, the drones are randomly generated and the queen selects a drone using the following annealing function:

$$\text{Prob}(Q, D) = e^{\left(\frac{-\Delta f}{s(t)}\right)} \tag{1}$$

where Prob (D, Q) is the probability of adding the sperm of drone D to the spermatheca of the queen Q that is, the probability of a successful mating, Δf is the absolute difference between the fitness of drone (D) and the fitness of the queen (Q), and the $S(t)$ is the speed of queen at time "t". After each transition of mating, the queen's speed and energy which at the beginning of her mating flight are high, decline according to the following equations [Page, 1980]:

$$\text{Speed } (t+1) = \beta \times \text{Speed } (t) \tag{2}$$

$$\text{Energy } (t+1) = \beta \times \text{Energy } (t) \tag{3}$$

where β is the decreasing factor (β=[0,1]).

Initially the speed of the queen is generated at random. At the start of a mating flight, drones are generated randomly and the queen selects a drone using the probabilistic rule (Niknam, 2011). If the mating is successful (i.e. the drone passes the probabilistic decision rule), the drone's sperm is stored in the queen's spermatheca (Page, 1980). Workers adopt some heuristic mechanisms such as crossover or mutation to improve the brood's genotype. The fitness of the resulting genotype is determined by evaluating the value of the objective function of the brood genotype.

The following stages are the principles of the HBMO algorithm (Niknam *et al.*, 2011; Niazkar and Afzali, 2015b; Afzali 2016):

- Starting the algorithm with the mating flight, where a queen (best solution) selects drones probabilistically to form the spermatheca (list of drones).
- Selecting a drone randomly for broods creation,
- Creating new broods by crossover the drone's genotypes with the queens,
- Using workers to conduct random search on broods (trial solutions),
- Adapting worker's fitness based on the amount of improvement achieved on the broods,
- Replacing the weaker queen by the fitter broods.

2.1. Modified HBMO (MHBMO)

In the original form of the HBMO algorithm, a random population of broods is generated based on mating between the queen and the drones stored in the queen's spermatheca matrix. For the generation of i^{th} brood, the i^{th} individual of the queen's spermatheca matrix is randomly selected. Afterward, the j^{th} brood will be generated with the following equations.

$$X_{Queen} = X_{best} = [X^1_{best}, X^2_{best}, \ldots, X^n_{best}] \tag{4}$$

$$SP_i = [SP_i^1, SP_i^2, \ldots, SP_i^n] \quad (5)$$

$$X_{Broodj} = X_{best} + rand \times (X_{best} - SP_i)\ ;\ j=1, N_{brood} \quad (6)$$

where X_{Queen} is the queen's matrix, SP_i is the queen's spermatheca matrix, X_{Broodj} is the j^{th} brood; rand is random function generator, and N_{brood} is the number of broods.

The proposed algorithm of brood generation in the original HBMO often converges to local optima and this is a disadvantage of this method. In order to avoid it, a modified method has been proposed to improve the brood generation (Page, 1980). This method improves the mating process in original HBMO and is as Modified HBMO (MHBMO).

In the proposed modification, three sperms (SP_{k1}, SP_{k2}, SP_{k3}) are randomly selected from the queen's spermatheca so that $k_1 \neq k_2 \neq k_3$. Afterward, two improved drones will be calculated with the following equations.

$$X_{im1} = SP_{k1} + rand \times (SP_{k2} - SP_{k3}) \quad (7)$$

$$X_{im1} = [x_{im1}^1, x_{im1}^2, \ldots, x_{im1}^n] \quad (8)$$

$$X_{Brood} = [x_{Br1}^1, x_{Br1}^2, \ldots, x_{Br1}^n] \quad (9)$$

$$x_{Br1}^j = \begin{cases} x_{im1}^j; \text{ if } \gamma_1 \leq \gamma_2 \\ x_{SP_{k1}}^j; \text{ Otherwise} \end{cases} ;\ j=1,\ \ldots\ ,\ n \quad (10)$$

$$X_{im2} = X_{best} + rand \times (SP_{k2} - SP_{k3}) \quad (11)$$

$$X = [x_{im2}^1, x_{im2}^2, \ldots, x_{im2}^n] \quad (12)$$

$$X_{Brood2} = [x_{Br2}^1, x_{Br2}^2, \ldots, x_{Br2}^n] \quad (13)$$

$$x_{Br2}^j = \begin{cases} x_{im2}^j; \text{ if } \gamma_3 \leq \gamma_2 \\ x_{best}^j; \text{ Otherwise} \end{cases} ;\ j=1,\ \ldots\ ,\ n \quad (14)$$

In the above equations, Xi_{m1} and X_{im2} are the first and second improved new drones, x_{Br1}^j and x_{Br2}^j are the first and second generated brood, γ_1, γ_2 and γ_3 are random numbers in range 0 and 1. The best individual between X_{Brood1}, X_{Brood2} and that concluded in original HBMO is considered as a new brood.

2.2. The simulation steps in HBMO algorithm

To apply the proposed algorithm for optimum design of steel frames, the following steps must be considered (Esmi Jahromi and Afzali, 2014; Niazkar and Afzali, 2015b):

Step 1. *Determination of the range of the algorithm parameters.* In this step, the range of the following parameters must be defined: Size of the initial population (N_{ipop}), the speed of queen at the start of the mating flight ($S_{\max}$), the speed of queen at the end of the mating flight ($S_{\min}$), the speed reduction factor (β), the number of workers (N_{Worker}), the number of drones (N_{Drone}), the size of the queen's spermtheca (N_{Sperm}) and the number of broods (N_{Brood}) must be defined at the beginning of the algorithm.

In this study, the aforementioned parameters would be considered equal to 550, 10,000, 1, 0.981, 8, 30, 35, and 35, respectively. These values were calculated by trial and error method and they are in the range of values which have been used by other researchers such as Niknam *et al.* (2011).

Step 2. *Input data*. It includes W-shaped sections from a standard set of steel sections given by the AISC-LRFD specification (AISC, 2001).

Step 3. *Initial population generation*. In this step, an initial population will be generated randomly based on the previously defined constraints. In other words, the initial population comprises the W-shape sections from a standard set of steel sections given by the AISC-LRFD.

Step 4. *Objective function calculation*. In this step, the objective function is calculated for each member X_i. To be more precise, the total weight of steel frame is the sole objective function of the design problem.

Step 5. *Sorting*. The initial population must be sorted increasingly based on the calculated values of objective function in order to separate different castes of the colony.

Step 6. *Queen selection*. The member who has the minimum objective function value, which has the minimum weight, or the first member in the above sorted population matrix can be considered as the queen (X_{best}).

Step 7. *Queen speed generation*. The queen speed is generated randomly with the following equation:

$$S_{Queen} = rand \times (S_{\max} - S_{\min}) + S_{\min} \quad (15)$$

The maximum and the minimum values of the queen speed, $S_{\max}$ and $S_{\min}$ have been defined in step 1.

Step 8. *Drones population selection*. The population of drones (N_{Drone}) will be selected from the sorted initial population. The second member till the N_{Drone} member in the sorted matrix provided in step 5 would be formed the drone population matrix.

Step 9. *Queen's spermatheca matrix generation (mating flight).* At the start of the mating flight, the queen flies with her maximum speed. A drone is randomly selected from the population of drones. The mating probability is calculated based on the objective function values of the queen and the selected drone. A number between 0 and 1 is randomly generated and compared with the calculated probability. If it is less than the calculated probability, the drone's sperm is stored in the queen's spermatheca and the queen speed is decreased. Otherwise, the queen speed is decreased and another drone from the population of drones is selected until the queen reaches to her minimum speed or the queen's spermatheca is full.

Step 10. *Broods population generation*. In this paper as described above the breeding process in original HBMO is improved.

Step 11. *Improvement of the selected broods with the royal jelly by workers*. By implementing the heuristic functions and mutation operators the brood population can be improved. For this reason a number (equal to or less than N_{Worker}) of individuals are randomly generated around the i^{th} brood. Then the value of the objective function is evaluated for each individual. These broods play the role of randomly generated set of W-shape sections, which will be imported to the current set of W-shape sections to update the next population. The best individual among these generated broods will be replaced with the i^{th} brood.

Step 12. *Objective function calculation and sorting*. In this step, the objective functions are calculated and sorted for the new population as mentioned in steps 4 and 5.

Step 13. *Termination and criteria checking*. The termination criteria will be checked in this step. If all criteria are satisfied the algorithm will be finished, else N_{best} individuals must be selected among broods matrix. They will be considered as the new population and the algorithm must be started again until all the convergence criteria are met. The flow chart of the mentioned steps is shown in Fig. 1.

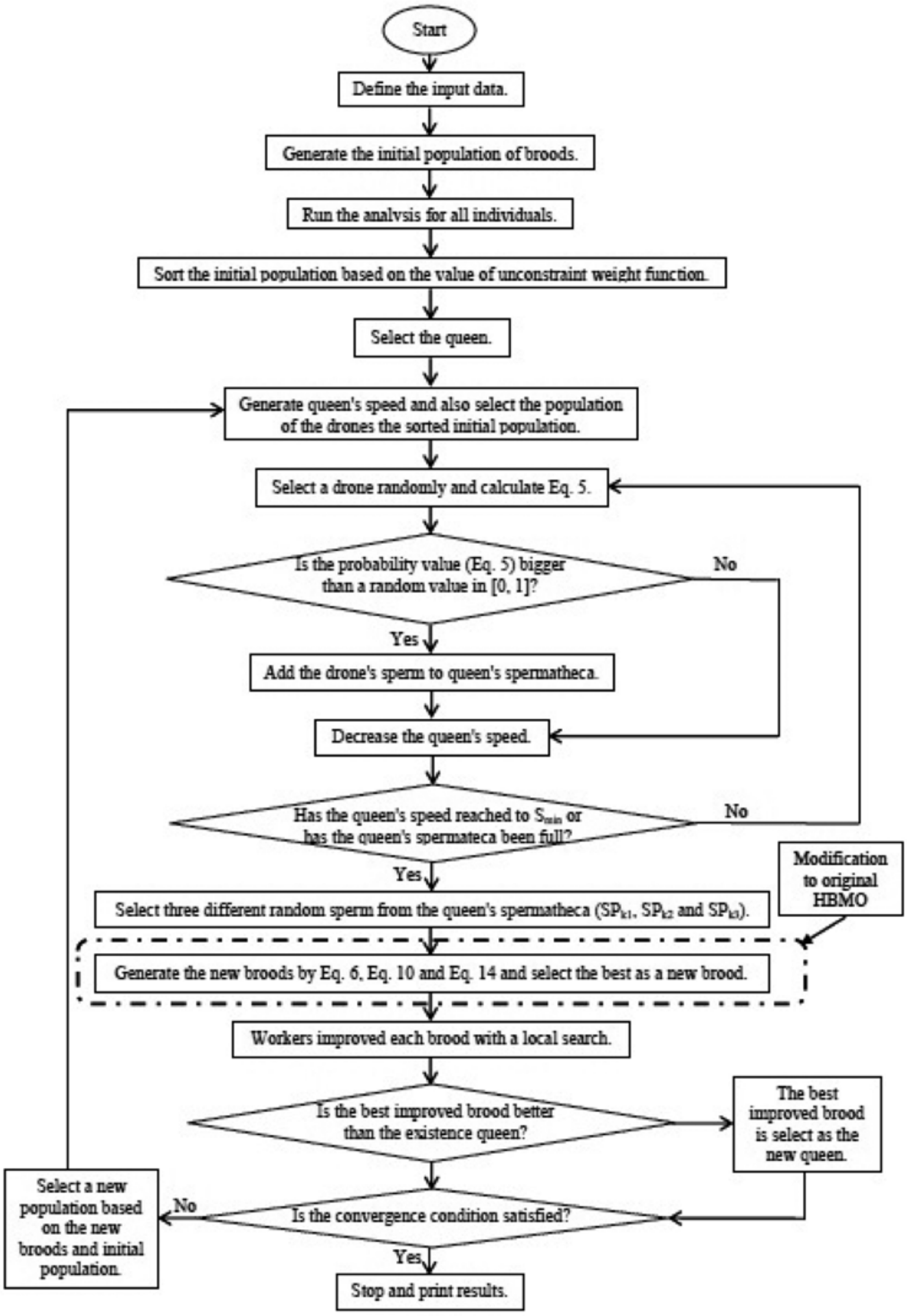

Figure 1. The flow chart of the MHBMO algorithm.

3. Formulation of the Optimum Design Problem

Design of steel frames requires selection of steel sections for its columns and beams from a standard steel section tables such that the frame obeys the serviceability and strength requirements specified by the code of practice. In the selection of these sections, both material and overall cost should be optimized (Saka, 2007). Hence, this design problem is a discrete optimum problem, which has the following mathematical form:

Find:

$$X_{Queen} = X_{best} = [X_{best}^1, X_{best}^2, \ldots, X_{best}^n]$$
$$= [A_1, A_2, \ldots, A_{ng}] \quad (16)$$

Objective function:

$$\text{Minimize } W(X) = \Sigma_{i=1}^{ng} A_i \Sigma_{j=1}^{mn} \rho_j L_j \quad (17)$$

Subjected to: (constraint functions)

$$c_k^{\sigma} \le 0 \quad k=1, \ldots, nc \quad (18)$$

$$c_r^{\sigma} \le 0 \quad r=1, \ldots, ns \quad (19)$$

$$1 \le A_i \le ms \quad i=1, \ldots, ng \quad (20)$$

where X is the design variables vector taken as the cross-section area of the each member group; ng is the total numbers of groups in the frame; $W(X)$ is the weight of the frame; mn is the total number of members in group i, ρ_j and L_j are density and length of member j, respectively; A_i is cross-sectional area of member i. The inequalities $c_k^{\sigma} \le 0$ and $c_r^{\sigma} \le 0$ represents the strength and displacement requirements imposed by the AISC-LRFD specification (AISC, 2001); ns and nc are the number of stories and the number of beam columns, respectively. Since A_i is selected W-shaped sections from a standard set of steel sections given by the AISC-LRFD specification (AISC, 2001). ms shows the total number of W-shaped sections considered in the design for group i. The strength constraints c_k^{σ}, for members subjected to axial force and bending are expressed according to AISC-LRFD as follows:

$$c_k^{\sigma} = \begin{cases} \dfrac{P_u}{\varphi P_n} + \dfrac{8}{9}\left(\dfrac{M_{ux}}{\varphi_b M_{nx}} + \dfrac{M_{uy}}{\varphi_b M_{ny}}\right) - 1 & \text{if } \dfrac{P_u}{\varphi P_n} \ge 0.2 \\ \dfrac{P_u}{2\varphi P_n} + \dfrac{8}{9}\left(\dfrac{M_{ux}}{\varphi_b M_{nx}} + \dfrac{M_{uy}}{\varphi_b M_{ny}}\right) - 1 & \text{if } \dfrac{P_u}{\varphi P_n} < 0.2 \end{cases} \quad (21)$$

in which P_u is the required axial strength (compression or tension); P_n is the nominal axial strength (compression or tension); M_{ux} and M_{uy} are the required flexural strengths about the major and the minor axes, respectively; M_{nx} is the nominal flexural strength about the major axis; M_{ny} is the nominal flexural strength about the minor axis (for two-dimensional frames, M_{uy}=0); φ is the resistance factor shown as φ_c and φ_t for compression (equal to 0.85) and tension (equal to 0.90), respectively; φ_b is the flexural resistance factor ,which is equal to 0.90.

The displacement constraints, $c_r^{\sigma} \le 0$, representing the inter-story drift of the multi-story frame are stated in the following equation:

$$c_r^{\delta} = \frac{\delta^*}{\sigma_{ru}} - 1 \quad \text{here } \delta^* = (\delta_r - \delta_{r-1}) \quad (22)$$

In Eq. (22), δ_r and δ_{r-1} are lateral deflection of two adjacent story level; δ_{ru} is the allowable lateral displacement (equal to h_r/300, where h_r is the storey height (Cm)).

4. Design Examples

The optimal designs of planar steel two-bay three-story, one-bay ten-story and three-bay twenty four-story frames, respectively, are evaluated by using the MHBMO to verify the suitability of the design procedure and to demonstrate the effectiveness and robustness of its. Since the mentioned frames are optimized by the other researchers using different algorithms, i.e. the genetic algorithm (GA) (Pezeshk *et al.*, 2000), the ant colony optimization (ACO) (Camp *et al.*, 2005), the harmony search (HS) (Degertekin, 2008), the improved ant colony optimization (IACO) (Kaveh and Talatahari, 2010) and teaching-learning based optimization (TLBO) (Toğan, 2012), therefore, the results of the MHBMO algorithm are compared to those of GA, ACO, HS, IACO and TLBO.

An approximation formula, $K_x = \sqrt{\dfrac{1.6G_A G_B + 4(G_A + G_B) + 7.5}{G_A + G_B + 7.5}}$, proposed by Dumonteil (1992) is used to calculate the member effective length factors, K_x, depending on the relative stiffness of a member at its two ends, G_A, G_B. Designs of examples are obtained selecting appropriate W-shaped sections from the AISC-LRFD specification (AISC, 2001).

4.1. Two-bay three-story frame design

Geometrical properties and load case of two-bay three-story frame consisting of 15 members planar frame is illustrated in Fig. 2. All members were assumed to be constructed from a material with the Young modulus, E, is 29,000 ksi and a yield stress, f_y, equal to 36 ksi. The objective of the problem is to minimize the weight of the structure and the constraints (excluding displacements) are imposed on member stresses in accordance with the AISC-LRFD specification (AISC, 2001).

Members of the frame are collected into two groups, which consist of six beams and nine columns. In the design, the beams are chosen from a list with 267-W shaped sections while the columns are limited to W10 sections resulting in 18-W shapes.

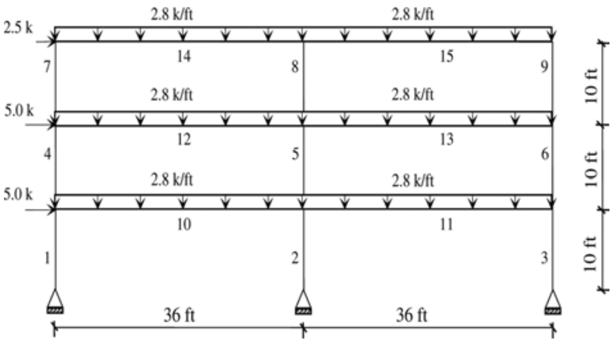

Figure 2. Topology of two-bay three-story frame.

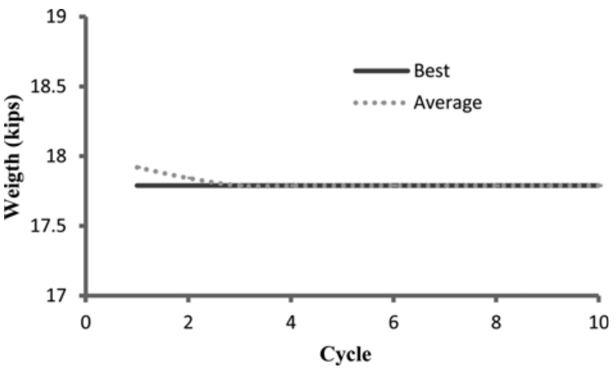

Figure 3. Convergence history of two-bay three-story frame.

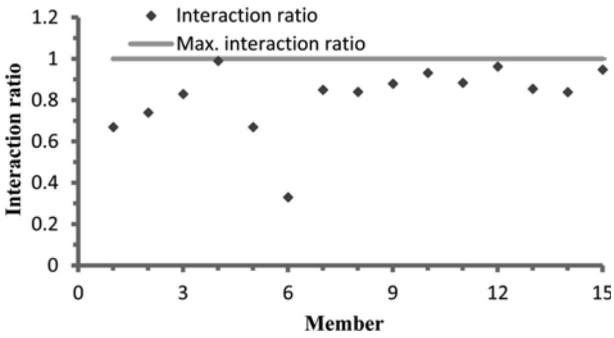

Figure 4. Interaction ratio of members of two-bay three-story frame.

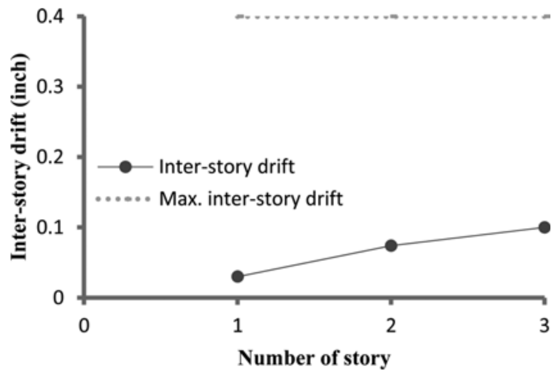

Figure 5. Inter-story drift of two-bay three-story frame.

The effective length factors, K_x, of the members are calculated from the approximate equation proposed by Dumonteil (1992). For each column, $K_{y'}$ the out-of-plane effective length factor is considered as 1.0. The out-of-plane effective length factor for each beam member is specified as one-sixth of the span length.

Table 1 summarizes the best designs obtained by Pezeshk *et al.* (2000) using Genethic Algorithm (GA), Camp *et al.* (2005) using Ant Colony Optimization (ACO), Degertekin (2008) using the Harmony Search (HS), and Toğan (2012) using Teaching-Learning Based Optimization (TLBO) and the MHBMO algorithm explained in this study.

The MHBMO algorithm requires approximately 650 frame analysis in order to yield the best optimum design (1 iteration with a 650 analysis enables to reach the best optimum design).

The convergence rate of the problem is demonstrated in the design history graph given in Fig. 3, whereas the interaction ratio of the members at the best solution and the inter-story drift of the mentioned frame are shown in Figs. 4 and 5, respectively. Not only inter-story drift constraints but also stress constraints are dominant at the optimum design in this frame.

Table 1 shows the optimum element designed for columns and beams and the optimum weight of the two-bay three-story frame. According to Table 1, the optimum weight achieved in this study is 17,789 kg and is equal to the TLBO results, which is lighter than the others. Hence, the MHBMO algorithm surprisingly yields the best answer or the optimal weight in the first iteration after 650 frame analyses.

4.2. One-bay ten-story frame design

Geometrical properties and load case of one-bay two-story frame is illustrated in Fig. 6. The frame consists of 30 members and they are organized into 9 groups due to fabrication conditions. The corresponding member groups,

Table 1. Designs for two-bay, three-story frame

Element group	Member	AISC W-shapes				
		GA (Pezeshk *et al.*, 2000)	ACO (Camp *et al.*, 2005)	HS (Degertekin, 2008)	TLBO (Toğan, 2012)	MHBMO (This study)
1 (beam)	10-15	W24×62	W24×62	W21×62	W24×62	W24×62
2 (column)	1-9	W10×60	W10×60	W10×54	W10×49	W10×49
Weight (lb)		18,792	18,792	18,292	17,789	17,789

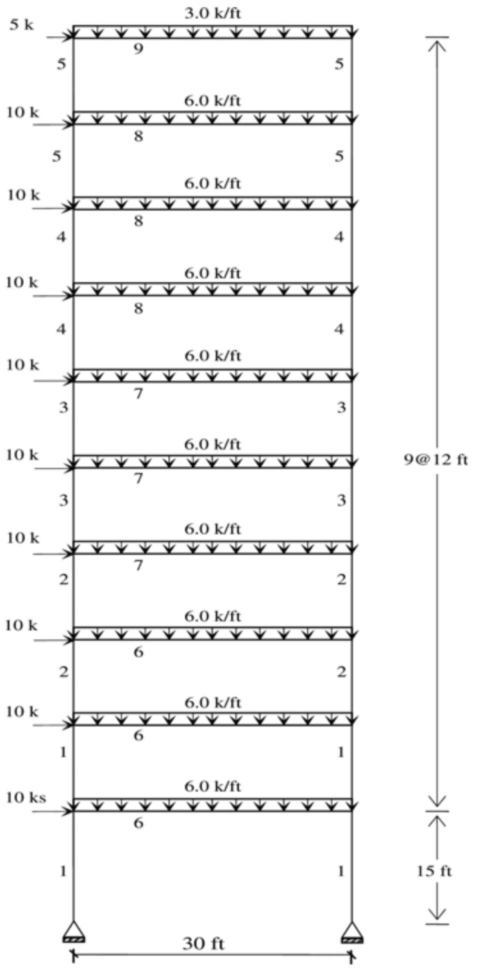

Figure 6. Topology of one-bay ten-story frame.

the dimension of the frame and the loading are shown in the Fig. 2. All members were assumed to be constructed from a material with the Young modulus, E, is 29,000 ksi and a yield stress, fy, is 36 ksi. The design is obeyed the AISC-LRFD specification (AISC, 2001) and a displacement constraint considered as: Inter-story drift < story height/300.

All 267-W sections is used the groups organized for beam members, while the column element groups is chosen from W14 and W12 sections. The effective length factors, K_x, of the members are calculated from the approximate equation proposed by Dumonteil (1992) when the out-of-plane effective length factor K_y is considered as 1.0. The out-of-plane effective length factor for each beam member is specified as one-fifth of the span length.

The MHBMO algorithm requires approximately 3600 frame analysis in order to yield the best optimum design (31 iteration with a 3600 frame analysis enables to reach the best optimum design) is more than 3000 and 2500 frame analyses required by GA (Rahami *et al.*, 2008) and IACO (Kaveh and Talatahari, 2010), and is lower than the 3690, 8300 and 4000 frame analyses required by HS (Degertekin, 2008), ACO (Camp *et al.*, 2005) and TLBO (Toğan, 2012). The average weight of the frame in the total of 31 iterations is 69,767.8 lb, with a standard deviation of 7,678.71 lb. The average weight in the final iteration is 61,644.1 lb, with a standard deviation of 52.2 lb. The best frame design that weighs 61,617 lb developed by the MHBMO and the other algorithms are presented in Table 2. According to Table 2, the best MHBMO design results is 5.4% less than the design of GA (Rahami *et al.*, 2008) and 1.6% less than the design of ACO (Camp *et al.*, 2005). Furthermore, the MHBMO algorithm produces lighter design to the design reported by HS (Degertekin, 2008) and TLBO (Toğan, 2012) (Table 2). Hence, the MHBMO algorithm achieved the best solution for optimum design of one-bay ten-story frame.

Figure 7 shows the design history for the best optimum design frame weight of 30 designs for the one-bay ten-story frame. Figures 8 and 9 shows the interaction ratio of members and the inter-story drift of the three-bay 24-story frame, respectively. As it is illustrated in Figs. 8 and 9, not only the inter-story drift constraints but also the

Table 2. Designs for one-bay, ten-story frame

Element group	AISC W-shapes					
	GA (Pezeshk *et al.*, 2000)	ACO (Camp *et al.*, 2005)	HS (Degertekin, 2008)	IACO (Kaveh and Talatahari, 2010)	TLBO (Toğan, 2012)	MHBMO (This study)
1 (column 1-2S)	W14×233	W14×233	W14×211	W14×233	W14×233	W14×233
2 (column 3-4S)	W14×176	W14×176	W14×176	W14×176	W14×176	W14×176
3 (column 5-6S)	W14×159	W14×145	W14×145	W14×145	W14×145	W14×145
4 (column 7-8S)	W14×99	W14×99	W14×90	W14×90	W14×99	W14×99
5 (column 9-10S)	W12×79	W12×65	W14×61	W12×65	W12×65	W14×61
6 (beam 1-3S)	W33×118	W30×108	W33×118	W33×118	W30×108	W30×108
7 (beam 4-6S)	W30×90	W30×90	W30×99	W30×90	W30×90	W30×90
8 (beam 7-9S)	W27×84	W27×84	W24×76	W24×76	W27×84	W27×84
9 (beam 10S)	W24×55	W21×44	W18×46	W14×30	W21×44	W21×44
Weight (lb)	65,136	62,610	61,864	61,820	61,813	61,617

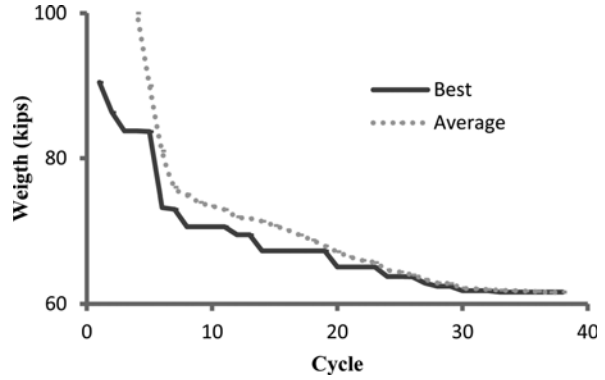

Figure 7. Convergence history of one-bay ten-story frame.

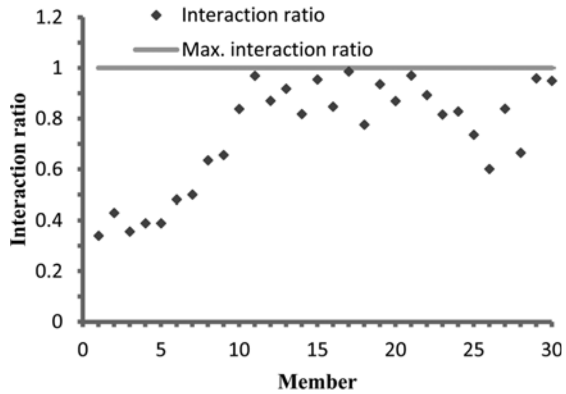

Figure 8. Interaction ratio of members of one-bay ten-story frame.

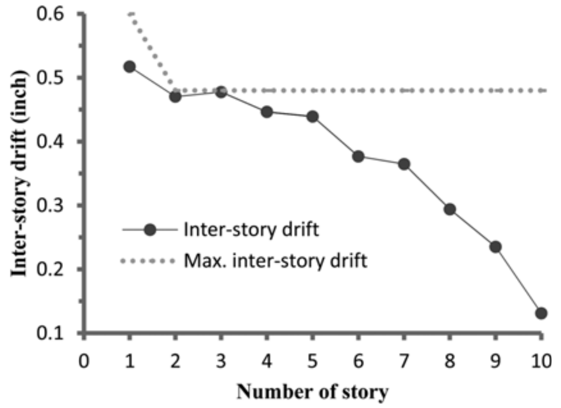

Figure 9. Inter-story drift of one-bay ten-story frame.

stress constraints are dominant at the optimum design. In other words, these constraints were successfully satisfied in the process of optimum design of steel frames.

4.3. Three-bay 24-story frame design

Figure 10 shows the configuration of the three-bay 24-story frame consisting of 168 members and its node, element numbering patterns and the loading. The loads are W= 5761.85 lb, w1=300 lb/ft, w2=436 lb/ft, w3=474 lb/ft and w4=408lb/ft. The members of planar frame are divided into 20 groups after linking in order to impose the fabrication condition on the construction of the 168 member frame. The outer columns and inner columns in every three story are grouped together. The beams of first and third bay on all floors are considered to be the same whereas the roof beams are grouped to be two different groups, resulting in four beam groups as shown in the Fig. 10. Each of the four beam element groups were chosen from all of the 267W-sections, whereas the 16 column member groups were selected from only W14 sections. The material properties are a modulus of elasticity of E=29,732 ksi and a yield stress of f_y=33.4 ksi. The frame is designed following the AISC-LRFD specification (AISC 2001) and uses an inter-story drift displacement constraint (inter-story drift<story height/300). The effective length factors, K_x, of the members are calculated from the approximate equation proposed by Dumonteil (1992) and the out-of-

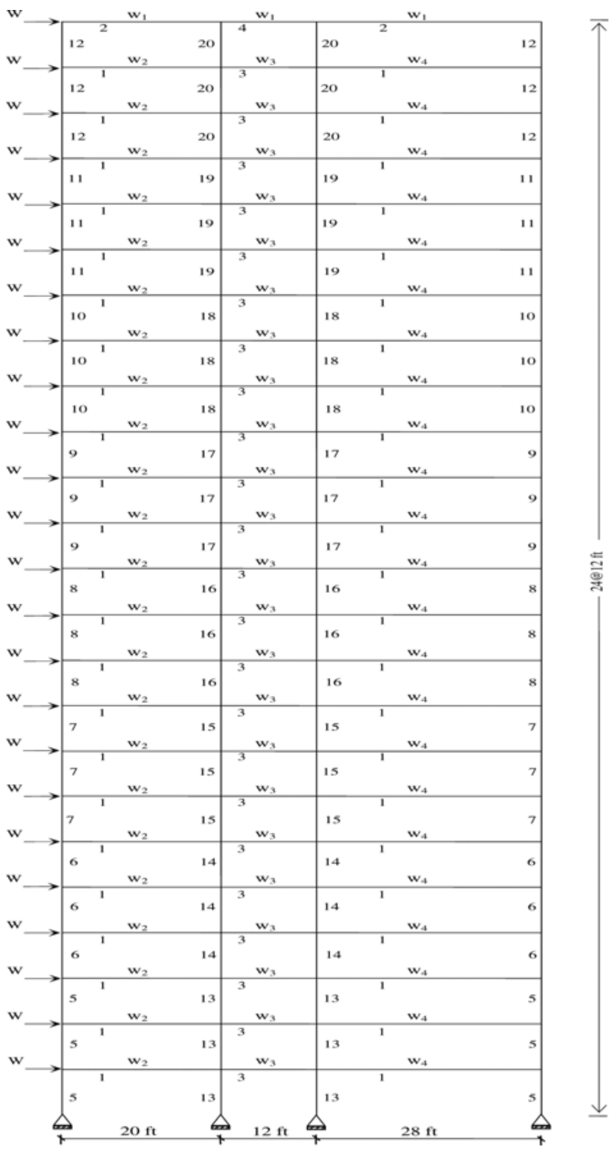

Figure 10. Topology of three-bay 24-story frame.

Table 3. Designs for three-bay, 24-story frame

Element group	AISC W-shapes				
	ACO (Camp *et al.*, 2005)	HS (Degertekin 2008)	IACO (Kaveh and Talatahari 2010)	TLBO (Toğan 2012)	MHBMO (This study)
1 (beam 1-23S, bay 1,3)	W30×90	W30×90	W30×99	W30×90	W30×90
2 (beam 24S, bay 1,3)	W8×18	W10×22	W16×26	W8×18	W8×18
3 (beam 1-23S, bay 2)	W24×55	W18×40	W18×35	W24×62	W24×55
4 (beam 24S, bay 2)	W8×21	W12×16	W14×22	W6×9	W14×22
5 (column 1-3S, E)	W14×145	W14×176	W14×145	W14×132	W14×145
6 (column 4-6S, E)	W14×132	W14×176	W14×132	W14×120	W14×120
7 (column 7-9S, E)	W14×132	W14×132	W14×120	W14×99	W14×99
8 (column 10-12S, E)	W14×132	W14×109	W14×109	W14×82	W14×82
9 (column 13-15S, E)	W14×68	W14×82	W14×48	W14×74	W14×68
10 (column 16-18S, E)	W14×53	W14×74	W14×48	W14×53	W14×53
11 (column 19-21S, E)	W14×43	W14×34	W14×34	W14×34	W14×30
12 (column 22-24S, E)	W14×43	W14×22	W14×30	W14×22	W14×22
13 (column 1-3S, I)	W14×145	W14×145	W14×159	W14×109	W14×120
14 (column 4-6S, I)	W14×145	W14×132	W14×120	W14×99	W14×109
15 (column 7-9S, I)	W14×120	W14×109	W14×109	W14×99	W14×99
16 (column 10-12S, I)	W14×90	W14×82	W14×99	W14×90	W14×90
17 (column 13-15S, I)	W14×90	W14×61	W14×82	W14×68	W14×68
18 (column 16-18S, I)	W14×61	W14×48	W14×53	W14×53	W14×53
19 (column 19-21S, I)	W14×30	W14×30	W14×38	W14×34	W14×30
20 (column 22-24S, I)	W14×26	W14×22	W14×26	W14×22	W14×22
Weight (lb)	220,465	214,860	217,464	203,008	202,754

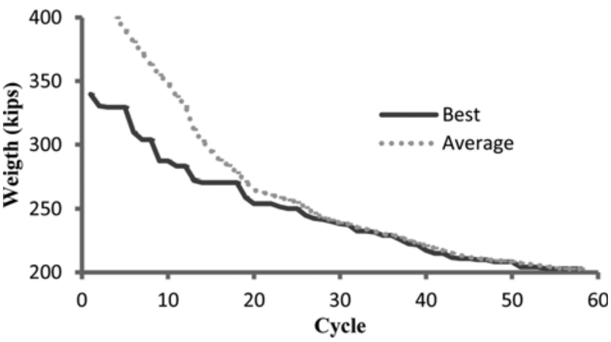

Figure 11. Convergence history of three-bay 24-story frame.

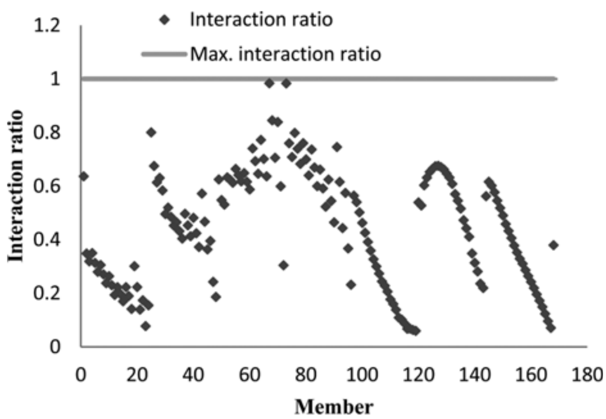

Figure 12. Interaction ratio of members of three-bay 24-story frame.

plane effective length factor, K_y, is considered as 1.0. All columns and beams are considered unbraced along their lengths. The optimum W-sections designation obtained by the MHBMO method and also the other methods are given in Table 3. The average weight of the frame in the total of 52 iterations is 252,257.288 lb, with a standard deviation of 38,108.06 lb. The average weight in the final iteration is 202,894.2 lb, with a standard deviation of 191.2 lb.

The optimum designs for three-bay, 24-story frame using the MHBMO algorithm and four other optimization technique is shown in Table 3. Based on Table 3, the design obtained by the MHBMO algorithm is 0.12% lighter than the minimum value obtained by the others. The lightest MHBMO design results in a frame that weighs 202,754 lb, is 8.7, 5.9, 7.2, and 0.12% lighter than the one obtained using ACO (Camp *et al.*, 2005), HS (Degertekin, 2008), IACO (Kaveh and Talatahari, 2010), and TLBO (Toğan, 2012), respectively. The MHBMO algorithm requires approximately 6000 frame analysis in order to yield the best optimum design (52 iterations with 6000 analysis frame). Although the required analyses number for the frame is more than 3500 analyses required by IACO, ACO and HS, except the 12000 analyses required by

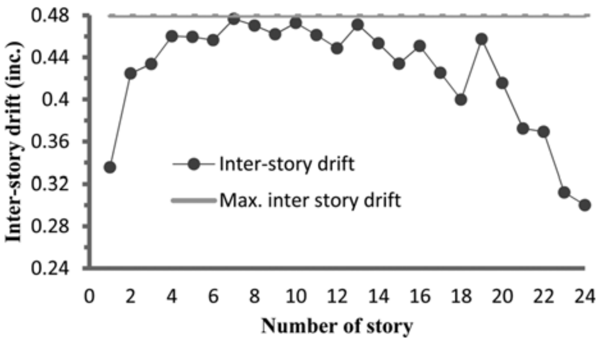

Figure 13. Inter-story drift of three-bay 24-story frame.

TLBO, it can be expressed that MHBMO algorithm exhibits more robustness and efficiency from the point of view of the best optimum design. Design history of number of iteration for the best optimum and average design of steel frame with MHBMO is illustrated in Fig. 12.

Figures 12 and 13 shows the interaction ratio of the members and the inter-story drift for each story of the three-bay 24-story frame, respectively. According to Figs. 12 and 13, not only the inter-story drift constraints but also the stress constraints are dominant at the optimum design, respectively. Finally, it can be concluded that the MHBMO algorithm achieved the best optimum design for all three examples, which shows the applicability of this algorithm for optimum design of steel structures.

5. Conclusions

Recently, some metaheuristic methods have been used as optimization tools for solving various engineering problems. In this study, the Modified Honey Bee Mating Optimization (MHBMO) algorithm was applied to develop an optimum design method for moment resisting steel frames. This algorithm is effective and also mathematically simple in finding the optimum solution of combinational problems. The objective function of the design process was minimizing the weight of steel structures, which was subjected to both strength- and displacement-requirement constraints. Three typical steel frames, which were selected from the literature, was designed using the MHBMO algorithm and the results were compared with the available ones in the literature. With regard to the results of the three different benchmark type frame optimization problems, the MHBMO algorithm not only achieved the best optimum results, but also is an efficient, suitable and applicable optimization method for solving constrained discrete problems. Finally, it can be concluded that this algorithm is a robust technique and demonstrates outstanding performance in optimum design of steel structures.

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