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OPTIMUM DESIGN OF SKELETAL STRUCTURES USING METAHEURISTICS: A SURVEY OF THE STATE-OF-THE-ART

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Abstract

During the past decades, inherent complexity of practical structural optimization problems motivated the researchers to develop efficient and robust optimization techniques. Undoubtedly, most of the recently developed optimization algorithms for optimum design of skeletal structures belong to the class of stochastic search algorithms or metaheuristics. This study is an attempt to outline the state-of-the-art in optimum design of skeletal structures as well as today's main concerns in this field. Some of the most recent applications of metaheuristics are summarized, and a brief conclusion of today's trend towards the computationally enhanced techniques is provided.

Keywords: Structural design, skeletal structures, metaheuristic techniques, sizing optimization, steel structures.

1. Introduction

Typically, an optimal design problem is composed of three basic elements: (i) objective function, (ii) design variables, and (iii) constraints. In structural design optimization usually weight or cost of the structure is taken as the objective function of the problem. Here, the fundamental aim is to minimize the final weight or cost of the structure which is a function of the design variables. The design variables are those parameters which are to be determined by the designer in order to generate an optimal solution. Furthermore, in practical applications achieving an optimum design should be carried out with respect to a set of strength and serviceability limitations i.e. design constraints.

In the literature, classifying the structural optimization problems is basically carried out regarding the type of design variables involved. It is worth mentioning that since optimum design of continuum structures is out of the scope of this study, the followings explicitly cover optimum design of skeletal structures (either truss or frame structures). Generally, optimum design of skeletal structures is divided into three main categories as sizing, shape, and topology optimization. In sizing optimization the cross sectional areas of structural members are considered as design variables. This can further be divided into two subcategories in terms of the nature of the design variables employed: continuous and discrete. In continuous sizing optimization any positive value can be assigned to cross sectional areas of elements. However, this is usually not the case in practical applications, where structural members should be adopted from a set of available sections. The latter is addressed to discrete sizing optimization. In shape optimization, the best positions of a selected group of joints in a structure are determined. Due to practical aspects this type of design optimization is usually involved in optimum design applications of truss structures rather than frames. In both the aforementioned optimization categories topology of a structure is assumed to be fixed. However, it is sometimes more expedient to search for the optimum topology of a structure, which entails considering the presence or absence of structural components, such as elements and nodes.

Since in practical sizing optimization of skeletal structures usually the structural members are to be adopted from a set of available sections, the design problem turns into a discrete sizing optimization. Here the aim is to seek for the best set of ready sections which yield the optimum design. Although for a given structure in fact the number of candidate solutions is numerically limited, however, in real world applications performing an exhaustive search is not possible in a timely manner. Therefore, structural optimization techniques have been proposed for locating the optimum or a reasonably good near optimum solution through investigating a portion of the design space in a reasonable computational time. These techniques as well as their applications in design optimization of structural systems are outlined in the following sections.

2. Structural Optimization Techniques

During the past decades, inherent complexity of practical structural optimization problems motivated the researchers to develop efficient and robust optimization techniques. Basically, structural optimization methods can be divided into two main categories: (i) traditional methods (ii) modern techniques. Two main categories of traditional structural optimization methods include mathematical programming and optimality criteria approaches, whereas heuristics or metaheuristic search techniques are referred to as the modern structural optimization methods. An overview of these techniques is provided in this section as follows. Mathematical programming techniques are amongst the well known classes of structural optimization techniques which work based on gradients of the objective function. The basic idea is to move in the negative direction of the gradient of the objective function to find a more promising candidate design. Many studies have been conducted on application of mathematical programming techniques in structural design optimization so far [1-4]. However, it is generally convinced that mathematical programming techniques are not efficient for optimum design of structural systems having numerous design variables. Another class of traditional structural optimization techniques covers optimality criteria methods. Typically in optimality criteria methods first a set of necessary optimality criteria (such as Kuhn-Tucker conditions) are derived for the design. Next, in order to generate an optimum design a recursive algorithm is employed to update the structural members for satisfying the optimality criteria. Early works on optimality criteria methods are due to Prager et al. [5], Prager [6], and Venkayya et al. [7]. Later, numerous variants of the optimality criteria methods are applied to optimum design of pin-jointed (Feury and Geradin [8], Fleury [9], Saka [10]) and frame structures (Tabak and Wright [11], Khan [12], Chan et al. [13]).

It is worth mentioning that the well known fully stressed design (FSD) (Gallagher [14], Patnaik et al. [15]) can be also considered as a simple stress-ratio optimality criteria technique which can only deal with stress constraints. An extension of FSD to handle both stress and displacement constraints is fully utilized design (FUD). The FUD includes two main steps (i) providing a FSD considering stress constrains (ii) prorating the FSD to obtain the FUD. The proportion parameter is computed with respect to the most violated displacement constraint. Although FUD is capable of generating a feasible solution through a small number of structural analyses, the obtained solution can be an overdesign. Patnaik et al. [15] developed a modified fully utilized design (MFUD) using the integrated force method (IFM) of structural analysis [16], however the study was limited to truss structures. The MFUD technique which can be also developed using the displacement method of structural analysis [15] employs some basic concepts of structural mechanics for optimal sizing of truss structures under both stress and displacement constraints. Hence, further research on application of the MFUD in practical optimum sizing of truss structures seems fruitful.

Basically, traditional structural optimization techniques i.e. mathematical programming and optimality criteria are developed for handling continuous design variables, hence, they are not effective for tackling practical discrete optimization instances. Furthermore, gradient based formulations of such methods entail different types of approximations which sometimes are far from the reality. Therefore, due to the shortcomings of traditional techniques in handling real world design optimization instances, in the recent decades, stochastic search techniques or metaheuristics have received an increasing attention and found plenty of applications in structural optimization field. In general, metaheuristic techniques, such as genetic algorithms (GAs) [17], particle swarm optimization (PSO) [18], ant colony optimization (ACO) [19], etc., borrow their working principles from natural phenomena [20]; and follow non-deterministic search strategies in locating the optimum solutions. The rising popularity of these techniques arise from (i) the lack of dependency on gradient information; (ii) inherent capability to deal with both discrete and continuous design variables; and (iii) automated global search features to produce near-optimum solutions (if not the global optimum) for complicated problems. In addition, the simplicity in their coding makes it possible to avoid cumbersome formulations frequently encountered with traditional structural optimization technique, and renders them ideal and prevalent tools for structural optimization applications. The state-of-the-art reviews of metaheuristic algorithms and their applications in structural optimization problems can be found in Saka [21], Lamberti and Pappalettere [22], Saka and Geem [23], and Hare et al. [24].

3. Metaheuristics Based Structural Optimization

Indeed, in the recent years, most of the optimization algorithms developed for optimum design of truss and frame structures belong to the class of stochastic search algorithms or metaheuristics. Besides various inspiration resources reported in the literature for development of metaheuristic search techniques, in fact these techniques have similar characteristics. Basically, a metaheuristic structural optimization algorithm aims to locate the global optimum in the solution space through generating candidate solutions in an iterative way. Roughly speaking, the fundamental idea is to seek the vicinity of more promising candidate designs found so far to drive the search towards more reliable portions of the solution space. Since working principals of these techniques are somewhat identical, a general description is provided here. Detailed descriptions of various types of metaheuristic algorithms can be found in [20].

Typically, a metaheuristic structural optimization algorithm initiates with a population of randomly generated candidate designs. Then in order to investigate the quality of generated designs, each candidate design is evaluated with respect to a merit function which can be the objective function of the problem. Once merit or fitness of each candidate design is computed, new candidate designs can be generated using the obtained information from the formerly generated designs. Generally, different mechanisms and operators are utilized for generating a new population of solutions to guide the search towards the optimum. In fact the key difference between the algorithms is in the way that they propose the next move in the solution space. In metaheuristics generation of new populations is iteratively performed until a predefined termination criterion, which is usually the maximum number of iterations, is met. The last iteration of a metaheuristic algorithm is expected to include the optimum or a reasonably good near optimum design. Many studies have been conducted on structural optimization using metaheuristics so far. Some of the most recent applications of these algorithms in optimum design of truss and frame structures are outlined as follows.

In fact GAs [17] are the most well known metaheuristic algorithms frequently employed for structural optimization applications. Kameshki and Saka [25] studied the effect of bracing on the optimum design of planar steel frames using GAs. In their study, first, a 15 story frame was designed assuming rigid beam column connections and fix supports, as well as rigid frame with pin supports. Then the same frame, with pin supports, was designed assuming pin beam-column connections with four types of frequently used bracing systems. Through investigating X-bracing, X-bracing with outrigger truss, V-bracing and Z-bracing systems they presented a clear numerical comparison among the minimum weights obtained for all the aforementioned systems. According to the reported results X-bracing provided the minimum weight frame in comparison to the other considered structural systems.

Kameshki and Saka [26] presented a GA for optimum design of steel frames with semi-rigid connections based on BS 5950 (1990) [27] specifications. Considering the optimum design of two unbraced steel frames with end plate connection without column stiffeners, it was deducted that the semi-rigid connection modeling produces lighter designs. In their work the number of investigated semi-rigid connections was limited to one type. In a more comprehensive study, Kameshki and Saka [28] evaluated the effect of connection flexibility and the geometric non-linearity of the frame members in the optimum design of planer steel frames. A GA based approach was employed for optimization of three unbraced steel frames with rigid and three different types of semi-rigid connections. It was demonstrated that considering the geometric nonlinearity, in the analysis stage, leads to lighter frames in case of rigid connections.

Kaveh and Kalatjari [29] employed the force method for structural analysis stage of a genetic algorithm based structural optimization technique. Considering optimum design of truss structures they demonstrated the computational efficiency of the proposed method. Hayalioglu and Degertekin [30] developed a genetic algorithm for cost efficient design of steel frames with semi-rigid connections and column bases. The optimization results of three planar steel frames using eight different types of semi-rigid connections and column bases was compared to those obtained using rigid connections. According to the presented numerical results, instead of using rigid connections, sometimes choosing specific types of semi-rigid connections could to be more economical. It should be noted that, since the study does not cover seismic loading, the conclusion cannot be generalized for the steel frames exposed to seismic loads. Later, Degertekin et al. [31] investigated the efficiency of the tabu search and genetic algorithm in design optimization of geometrically nonlinear steel space frames based on the AISC-LRFD (1995) [32] specifications. According to the investigated examples, tabu search (TS) algorithm resulted in lighter designs. Recently, Kazemzadeh Azad et al. [33] developed a mutation based GA for sizing and shape optimization of planar and spatial truss structures. An adaptive tournament selection mechanism in combination with adaptive Gaussian mutation operators were used to achieve an effective search in the design space. The efficiency of the proposed GA was demonstrated using design examples of truss structures with both discrete and continuous design variables.

The PSO algorithm proposed by Kennedy and Eberhart [18] is another popular metaheuristic search technique with extensive applications in the field of structural design optimization. Fourie and Groenwold [34] applied the PSO algorithm to design optimization instances with sizing and shape variables and compared its performance to that of GA as well as three gradient based techniques. Considering optimum design of three truss structures and a torque arm the authors demonstrated the suitability of the PSO in tackling structural optimization problems. Perez and Behdinan [35] investigated the effect of different parameter settings on the efficiency of the PSO algorithm through optimal design of classical truss optimization instances. Li et al. [36, 37] proposed improved variants of the PSO as heuristic PSO algorithms for optimum design of truss structures. Further, Kaveh and Talatahari [38] developed a hybrid version of the PSO algorithm for discrete sizing optimization of truss structures and demonstrated its promising performance. Luh and Lin [39] used a two stage PSO algorithm for minimum weight design of truss structures. In their approach first a topology optimization is performed using a ground structure and next sizing and shape optimizations are carried out to locate the minimum weight design. Recently, Gomes [40] employed the PSO algorithm for sizing and shape optimization of truss structures with frequency constraints and reported promising performance of the technique.

Geem et al. [41] developed the harmony search (HS) algorithm as a new meta-heuristic technique. Later, Lee and Geem [42] used the algorithm for sizing optimization of truss structures and demonstrated its efficiency compared to conventional mathematical methods as well as genetic algorithm. They concluded that the algorithm can be also employed for optimum design of other types of structures such as frame, plate or shell structures. Saka [43] demonstrated the efficiency of the HS algorithm in optimum geometry design of single layer geodesic domes. In their approach the height of the dome crown was treated as a design variable along with the cross-sectional designations of dome members. Later, Carbas and Saka [44] employed the algorithm for design optimization of single layer network domes. Saka [45] used the HS algorithm for optimum design of steel sway frames. Recently, Hasancebi et al. [46] presented an adaptive harmony search algorithm for structural optimization and employed it for sizing optimization of a 162-member braced planar steel frame and a 744-member unbraced space steel frame. Unlike the standard HS algorithm where the control parameters are typically set to constant values, in their algorithm these parameters are adaptively tuned during the search to establish a tradeoff between the exploration and exploitation in the design space. They illustrated the efficiency of their adaptive approach through comparison of the obtained numerical results with those of four other metaheuristic algorithms.

Another novel metaheuristic algorithm is a nature-inspired method so called artificial bee colony (ABC) algorithm which is proposed by Karaboga [47]. One recent application of this algorithm in sizing optimization of planar and space truss structures is due to Hadidi et al. [48]. The authors proposed some modifications in the original algorithm and reported satisfactory results of optimum design of four truss structure examples. Sonmez [49] used a discrete ABC algorithm for optimum design of truss structures with up to 582 members and reported promising performance of the algorithm compared to the other well known metaheuristic techniques. Furthermore, Sonmez [50] employed the ABC algorithm with an adaptive penalty function approach for minimum weight design of truss structures with fixed geometries. Besides the available works in the literature on application of the ABC in optimum design of truss structures, further research is required to investigate the performance of the algorithm in optimum design of steel frames.

Erol and Eksin [51] introduced a new metaheuristic optimization method called Big Bang–Big Crunch (BB-BC) algorithm. Due to the simple algorithmic outline of the method as well as its efficiency in tackling practical optimization instances, it has become one of the popular metaheuristics of the recent years. The first application of the algorithm in optimum design of skeletal structures was carried out by Camp [52]. In his work the optimum design of planar and spatial truss structures was performed using a modified version of the algorithm. In order to increase the efficiency of the BB–BC algorithm, Camp [52] introduced a weighting parameter to control the influence of both the center of mass and the current global best solution on new candidate solutions. Further, a multiphase search strategy was employed to increase the quality of final solution. The study demonstrated the efficiency of the BB–BC algorithm in comparison to the previously reported GA, PSO, and ACO based approaches. Later, Kaveh and Abbasgholiha [53] adopted the Camp's strategy of generating new candidate solutions for design optimization of planar steel sway frames. Lamberti and Pappalettere [54] proposed an improved version of the BB-BC algorithm for weight minimization of truss structures and reported promising results using four benchmark truss optimization instances. Kaveh and Talatahari [55-57] developed hybrid versions of the BB-BC algorithm for optimum design of different types of skeletal structures. Recently, in Kazemzadeh Azad et al. [58] the success of BB-BC algorithm in benchmark problems of engineering optimization is investigated.

Charged system search (CSS) is a very recent meta-heuristic optimization algorithm proposed by Kaveh and Talatahari [59]. The authors employed the algorithm for optimum design of skeletal structures including three truss and two frame structures [60]. The study revealed the efficiency of the CSS in comparison to the other heuristic methods. In another study the authors applied a discrete version of the algorithm to sizing optimization of different types of truss structures with fixed configurations [61]. Furthermore, an enhanced version of the CSS algorithm is used for configuration optimization of truss structures in Ref. [62]. Additionally, the efficiency of the charged system search is demonstrated considering the optimum design of three benchmark examples of frame structures with up to 290 members by Kaveh and Talatahari [63].

Besides the above-mentioned algorithms, numerous metaheuristic search techniques have been also developed in the recent years to deal with challenging optimization problems [64, 65]. Due to the variety of metaheuristic techniques available in the literature of structural optimization, adopting an appropriate method for practical applications may turn into a confusing task. Therefore, comparison and performance evaluation of optimization algorithms can lessen the burden of choosing an efficient algorithm to deal with a given design optimization problem. In this regard, Hasançebi et al. [66] evaluated the performance of seven metaheuristic optimization algorithms in optimum design of real size pin jointed structures. The investigated algorithms include GA, simulated annealing (SA) [67], evolution strategies (ES) [68], PSO, tabu search (TS) [69], ant colony optimization (ACO) and HS. The algorithms were compared through design optimization of four real size truss structures according to the design limitations of AISC-ASD (1989) [70]. The study revealed the superiority of SA and ES to the other techniques in design optimization of truss structures. Later, Hasancebi et al. [71] investigated the performance of the above mentioned algorithms in design optimization of steel frames with rigid connections. In the studied three steel frame examples, the two best performances were related to ES and SA algorithms amongst the other techniques. The study provides general guidelines for future practical applications of metaheuristics in design optimization of steel frames.

4. Today's Dilemma in Practical Structural Optimization

Despite many studies conducted on developing efficient optimization algorithms for structural optimization applications, no unique method is accepted to be the most successful approach for optimum design of skeletal structures so far. Basically, two main factors determine the efficiency of a design optimization algorithm. The first criterion is optimality of the obtained final design and the second measure is speed of the algorithm in finding the optimum solution. The latter is highly dependent on the number of structural analysis required in the optimization process to locate the optimum or a relatively good near optimum solution. In spite of many advantageous characteristics of modern structural optimization techniques namely metaheuristics, the slow rate of convergence towards the optimum as well as the need for a high number of structural analyses are conceived as the downside of the search features of these techniques in structural optimization applications. It is known that response computations of designs sampled during a search process usually occupies 85-95% workload of a metaheuristic technique [72], and thus large number of structural analyses substantially increases the total computing time. Here, one solution to this is to reduce the total computational time by taking advantage of high performance computing methods, such as parallel or distributed computing methods. The idea in this approach is to distribute the total workload of the algorithm amongst multiprocessors of a single computer or within a cluster of computers connected to each other via local area network. In Hasançebi et al. [72] it is shown that a maximum speedup ratio between 12.2 and 16.8 can be achieved for three large-scale design examples solved using a cluster computing system consisting of 32 processors.

Another approach, which is more straightforward and easier to apply, is to develop efficient strategies for diminishing the number of structural analyses required in the course of optimization. The latter, can be carried out by proposing efficient optimization techniques that are able to locate a reasonable solution using fewer numbers of structural analyses, i.e. less computational effort [73].

Considering the above mentioned issues today there is a great demand for optimum design algorithms capable of handling practical design instances in a timely manner, of course without employing expensive high performance computing techniques.

5. Concluding Remarks

Although numerous studies demonstrate the applicability of modern optimization techniques in structural design optimization, still optimization is not established well in practical design of skeletal structures basically due to the fact that enormously time consuming procedures of modern techniques make structural engineers reluctant to use them in real world applications. The computational inefficiency of modern techniques makes it almost impossible to use them for large scale applications without utilizing expensive high performance computing techniques. As a result of this, structural engineers generally do not receive benefits of optimization in large scale applications wherein optimality of final designs are much more important in comparison to small size structures. In the other words, there is a great demand for robust and efficient algorithms capable of handling large scale systems without employing high performance computing techniques. Regarding this issue the new trend of structural design optimization is towards developing automated optimum design tools capable of locating promising solutions in a reasonable computational time for practical applications. There is a great need for robust and efficient algorithms capable of handling large scale systems in a timely manner.

References

[1] Belegundu, A.D., and Arora, J.S., A study of mathematical programming methods for structural optimization. Part II: Numerical results, *Int. J Numer Methods Eng*, 21(9), 1601–1623, 1985.

[2] Rashedi, R., and Moses, F., Application of linear programming to structural system reliability, *Comput Struct*, 24(3), 375–384, 1986.

[3] Hall, S.K., Cameron, G.E., and Grierson, D.E., Least-weight design of steel frameworks accounting for P-Δ effects, *J Struct Eng*, ASCE, 115(6), 1463–1475, 1989.

[4] Erbatur, F., and Al-Hussainy, M.M., Optimum design of frames, *Comput Struct*, 45(5–6): 887–891, 1992.

[5] Prager, W., and Shield, R. T., A general theory of optimal plastic design, *J Appl Mech,* 34(l), 184-186, 1967.

[6] Prager, W., Optimality criteria in structural design, Proceedings of National Academy for Science, vol. 61, no. 3, pp. 794–796, 1968.

[7] Venkayya, V. B., Khot, N. S., and Berke, L., Application of optimality criteria approaches to automated design of large practical structures, Proceedings of the 2nd Symposium on Structural Optimization, AGARD-CP-123, pp. 3-1–3-19, 1973.

[8] Feury, C., and Geradin, M., Optimality criteria and mathematical programming in structural weight optimization, *Comput Struct*, 8, 7–17, 1978.

[9] Fleury, C., An efficient optimality criteria approach to the minimum weight design of elastic structures, *Comput Struct*, 11, 163–173, 1980.

[10] Saka, M. P., Optimum design of space trusses with buckling constraints, Proceedings of 3rd International Conference on Space Structures, University of Surrey, Guildford, U.K., September, 1984.

[11] Tabak, E. I., and Wright, P. M., Optimality criteria method for building frames, *J Struct Division*, 107, 1327–1342, 1981.

[12] Khan, M. R., Optimality criterion techniques applied to frames having general cross-sectional relationships, *AIAA Journal*, vol.22, no. 5, pp. 669–676, 1984.

[13] Chan, C.-M., Grierson, D. E., and Sherbourne, A. N., Automatic optimal design of tall steel building frameworks*, J Struct Eng*, 121(5), 838–847, 1995.

[14] Gallagher, R.H., Fully stressed design. In: Gallagher, R.H., Zienkiewicz, O.C., (eds) Optimum structural design: theory and applications, Wiley, Chichester, 19–32, 1973.

[15] Patnaik, S.N., Gendy, A.S., Berke, L., Hopkins, D.A., Modified fully utilized design (MFUD) method for stress and displacement constraints*, Int J Numer Methods Eng*, 41, 1171–1194, 1998.

[16] Patnaik, S.N., Berke, L., Gallagher, R.H., Integrated force method versus displacement method for finite element analysis, *Comput Struct*, 38, 377–407, 1991.

[17] Goldberg, D.E., Samtani, M.P., Engineering optimization via genetic algorithm, Proceeding of the Ninth Conference on Electronic Computation, ASCE, New York, 471–482, 1986.

[18] Kennedy, J., Eberhart, R., Particle swarm optimization. In: IEEE international conference on neural networks, IEEE Press, 1942–1948, 1995.

[19] Dorigo, M., Optimization, learning and natural algorithms, PhD thesis, Dipartimento Elettronica e Informazione, Politecnico di Milano, Italy, 1992.

[20] Yang, X-S., Nature-inspired metaheuristic algorithms, UK, Luniver Press, 2008.

[21] Saka, M.P., Optimum design of steel frames using stochastic search techniques based on natural phenomena: a review, in Topping B.H.V., (Editor), Civil Engineering Computations: Tools and Techniques, Saxe-Coburg Publications, Stirlingshire, UK., 2007.

[22] Lamberti, L., and Pappalettere, C., Metaheuristic design optimization of skeletal structures: a review, Computational Technology Reviews, 4, 1–32, 2011.

[23] Saka, M.P., and Geem, Z.W., Mathematical and Metaheuristic Applications in Design Optimization of Steel Frame Structures: An Extensive Review, *Mathematical Problems in Engineering*, Article ID 271031, 2013. doi:10.1155/2013/271031.

[24] Hare, W., Nutini, J., Tesfamariam, S, A survey of non-gradient optimization methods in structural engineering, *Adv Eng Software* 59, 19–28, 2013.

[25] Kameshki, E. S., and Saka, M. P., Genetic algorithm based optimum bracing design of non-swaying tall plane frames, *J Construct Steel Res*, 57, 1081–1097, 2001.

[26] Kameshki, E. S., and Saka, M. P., Optimum design of nonlinear steel frames with semi-rigid connections using a genetic algorithm, *Comput Struct*, 79, 1593–1604, 2001.

[27] British Standards Institution, Structural use of steel works in building, Part 1, Code of practice for design in simple and continuous construction, hot rolled sections, BS 5950, London, 1990.

[28] Kameshki, E. S., and Saka, M. P., Genetic algorithm based optimum design of nonlinear planar steel frames with various semi-rigid connections, *J Construct Steel Res*, 59, 109–134, 2003.

[29] Kaveh, A., and Kalatjari, V., Genetic algorithm for discrete-sizing optimal design of trusses using the force method, *Int J Numer Meth Eng*, 55(1), 55–72, 2002.

[30] Hayalioglu, M. S., and Degertekin, S. O., Minimum cost design of steel frames with semi-rigid connections and column bases via genetic optimization, *Comput Struct*, 83(21–22), 1849–1863, 2005.

[31] Degertekin, S. O., Saka, M. P., and Hayalioglu, M.S., Optimal load and resistance factor design of geometrically nonlinear steel space frames via tabu search and genetic algorithm, *Eng Struct*, 30(1), 197–205, 2008.

[32] American Institute of Steel Construction, Manual of steel construction: load and resistance factor design, AISC, Chicago, 1995.

[33] Kazemzadeh Azad, S., Kazemzadeh Azad, S., and Kulkarni A.J., Structural optimization using a mutation based genetic algorithm, *Int J Optim Civil E*ng, 2 (1), 81-101, 2012.

[34] Fourie, P.C., Groenwold, A.A., The particle swarm optimization algorithm in size and shape optimization, *Struct Multidiscip Optim*, 23, 259–267, 2002.

[35] Perez, R.E., Behdinan, K., Particle swarm approach for structural design optimization, *Comput Struct*, 85, 1579–1588, 2007.

[36] Li, L.J., Huang, Z.B., Liu, F., Wu, Q.H., A heuristic particle swarm optimizer for optimization of pin connected structures, *Comput Struct*, 85, 340–349, 2007.

[37] Li, L.J., Huang, Z.B., Liu, F., A heuristic particle swarm optimization method for truss structures with discrete variables, *Comput Struct*, 87, 435–443, 2009.

[38] Kaveh, A., Talatahari, S., A particle swarm ant colony optimization for truss structures with discrete variables, *J Construct Steel Res*, 65, 1558–1568, 2009.

[39] Luh, G.C., Lin, C.Y., Optimal design of truss-structures using particle swarm optimization, *Comput Struct*, 89, 2221–2232, 2011.

[40] Gomes, H.M., Truss optimization with dynamic constraints using a particle swarm algorithm, *Expert Syst Appl*, 38, 957–968, 2011.

[41] Geem, Z. W., Kim, J. H., and Loganathan, G. V., A new heuristic optimization algorithm: harmony search, *Simulation*, 76(2), 60–68, 2001.

[42] Lee, K. S., and Geem, Z. W., A new structural optimization method based on the harmony search algorithm, *Comput Struct*, 82, 781–98, 2004.

[43] Saka, M. P., Optimum geometry design of geodesic domes using harmony search algorithm, *Adv Struct Eng*, 10, 595–606, 2007.

[44] Carbas, S., and Saka, M. P., Optimum design of single layer network domes using harmony search method, *Asian J Civ Eng*, 10(1), 97–112, 2009.

[45] Saka, M. P., Optimum design of steel sway frames to BS5950 using harmony search algorithm, *J Construct Steel Res*, 65(1), 36–43, 2009.

[46] Hasançebi, O., Erdal, F., and Saka, M. P., Adaptive harmony search method for structural optimization. *J Struct Eng,* ASCE, 136(4), 419–431, 2010.

[47] Karaboga, D., An idea based on honey bee swarm for numerical optimization, Technical Report TR06, Computer Engineering Department, Erciyes University, Turkey, 2005.

[48] Hadidi, A., Kazemzadeh Azad, S., Kazemzadeh Azad, S., Structural optimization using artificial bee colony algorithm, The 2nd International Conference on Engineering Optimization (Eng Opt), Lisbon, Portugal, 2010.

[49] Sonmez, M., Discrete optimum design of truss structures using artificial bee colony algorithm, *Struct Multidisc Optim*, 43, 85–97, 2011.

[50] Sonmez, M., Artificial bee colony algorithm for optimization of truss structures, *Appl Soft Comp*, 11, 2406–2418, 2011.

[51] Erol, O. K., and Eksin, I., A New optimization method: Big Bang–Big Crunch, *Adv Eng Software*, 37, 106–11, 2006.

[52] Camp, C.V., Design of space trusses using Big Bang–Big Crunch optimization, *J Struct Eng*, ASCE, 133, 999–1008, 2007.

[53] Kaveh, A., and Abbasgholiha, H., Optimum design of steel sway frames using big bang–big crunch algorithm, *Asian J Civ Eng*, 12, 293–317, 2011.

[54] Lamberti, L., and Pappalettere, C., A fast big bang-big crunch optimization algorithm for weight minimization of truss structures. In: Tsompanakis Y, Topping BHV, editors. Proceedings of the Second International Conference on Soft Computing Technology in Civil, Structural and Environmental Engineering, Stirlingshire, UK, Civil-Comp Press, 2011.

[55] Kaveh, A., and Talatahari, S., Size optimization of space trusses using big bang-big crunch algorithm, *Comput Struct*, 87, 1129–1140, 2009.

[56] Kaveh, A., and Talatahari, S., Optimal design of Schwedler and ribbed domes via hybrid big bang-big crunch algorithm, *J Construct Steel Res*, 66, 412–419, 2009.

[57] Kaveh, A., and Talatahari, S., A discrete big bang-big crunch algorithm for optimal design of skeletal structures, *Asian J Civ Eng*, 11, 103–123, 2010.

[58] Kazemzadeh Azad, S., Hasançebi, O., and Erol, O.K., Evaluating efficiency of big bang-big crunch algorithm in benchmark engineering optimization problems, *Int J Optim Civ Eng,* 1, 495–505, 2011.

[59] Kaveh, A., Talatahari, S., A novel heuristic optimization method: charged system search, *Acta Mech*, 213, 267–289, 2010.

[60] Kaveh, A., Talatahari, S., Optimal design of skeletal structures via the charged system search algorithm, *Struct Multidisc Optim*, 41, 893–911, 2010.

[61] Kaveh, A., Talatahari, S., A charged system search with a fly to boundary method for discrete optimum design of truss structures, *Asian J Civ Eng*, 11(3), 277–293, 2010.

[62] Kaveh, A., and Talatahari, S., An enhanced charged system search for configuration optimization using the concept of fields of forces, *Struct Multidisc Opt*, 43(3), 339–51, 2011.

[63] Kaveh, A., and Talatahari, S., Charged system search for optimal design of frame structures, *Appl Soft Comp*, 12(1), 382–393, 2012.

[64] Yang, X-S., A new metaheuristic bat-Inspired algorithm, In: J. R. Gonzalez et al. (Eds.), Nature Inspired Cooperative Strategies for Optimization (NISCO 2010), Studies in Computational Intelligence, Springer Berlin, Springer, pp. 65–74, 2010.

[65] Kaveh, A., Khayatazad, M., A new meta-heuristic method: Ray Optimization, *Comput Struct*, 112–113, 283–294, 2012.

[66] Hasançebi, O., Çarbas, S., Dogan, E., Erdal, F., and Saka, M.P., Performance evaluation of metaheuristic search techniques in the optimum design of real size pin jointed structures, *Comput Struct*, 87, 284–302, 2009.

[67] Kirkpatrick, S., Gerlatt, C.D., Vecchi, M.P., Optimization by Simulated Annealing, *Science*, 220, 671–680, 1983.

[68] Rechenberg, I., Cybernetic Solution Path of An Experimental Problem, Royal Aircraft Establishment, Library translation No. 1122, Farnborough, Hants., UK, 1965.

[69] Glover, F., Tabu Search-Part I, *ORSA Journal on Computing*, 1,190–206, 1989.

[70] AISC-ASD, Manual of steel construction-allowable stress design, ninth ed., Chicago, Illinois, USA, 1989.

[71] Hasançebi, O., Çarbas, S., Dogan, E., Erdal, F., Saka, M.P., Comparison of non-deterministic search techniques in the optimum design of real size steel frames, *Comput Struct,* 88, 1033–1048, 2010.

[72] Hasançebi, O., Bahçecioğlu, T., Kurç, Ö., and Saka, M.P. Optimum design of high-rise steel buildings using an evolution strategy integrated parallel algorithm, *Comput Struct*, 89, 2037–2051, 2011.

[73] Kazemzadeh Azad, S., Hasançebi, O., and Kazemzadeh Azad, S., Upper Bound Strategy for Metaheuristic Based Design Optimization of Steel Frames, *Adv Eng Software*, 57, 19–32, 2013.