An Innovative Method for Constraints Handling of Structural Optimization Problems Fuzzy-based Ideal Feasible Design Technique

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An Innovative Method for Constraints Handling of Structural Optimization Problems: Fuzzy-based Ideal Feasible Design Technique

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Abstract: In this paper, a specified constraint-handling technique for structures is proposed and developed. This new technique is based on fuzzy-logic and some mechanical properties of structures. Compared to commonly used penalty techniques, it does not require pre-tuning in parameters and it shows more stable results and requires considerable fewer iterations to converge without reducing the solution quality. Therefore, the new technique is more user friendly. Also, successful convergence to feasible solutions removes the necessity of using final local search approaches which required the designer to execute some manual try-and-errors to achieve a feasible acceptable design for reporting. Robustness of the proposed fitness function, called Fuzzy Ideal-Feasible-Design (FIFD) technique, is verified on three large scale steel frames using different meta-heuristic methods. Brilliant results show that FIFD is a revolution in handling design criteria that might be a significant step in commercializing optimum design among the practical users in construction markets.

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1 Introduction

Structural optimization is a constrained problem in which the constraints are design criteria mentioned in the related codes; while, almost all optimization methods are basically developed for exploring the search space to find extremums of objective functions with no constraints. Genetic Algorithm (GA) (by Holland [1]), Differential evolution (DE) (Storn and Price [2]), Particle Swarm Optimization (PSO) by Eberhart and Kennedy [3], Bat Algorithm (BA) proposed by Yang [4], Ant Colony Optimization algorithm (ACO) developed by Dorigo[5], Cuckoo Search (CS) proposed by Yang and Deb[6], Tabu search (Glover [7],[8]), Imperialist competitive algorithm (ICA) (Gargari [9]), Big bang-Big crunch (BB-BC) (Erol and Eksin [10]), Artificial Bee-colony algorithm (ABC) (Karaboğa [11]), Harmony search (HS) (Geem et al. [12]), Charged System Search algorithm (CSS) (Kaveh and Talatahari [13]) and chaos game optimization (CGO) (Talatahari and Azizi [14]) all perform in this way. Therefore, handling design criteria has been of utmost interests among structural engineers.

Not only structural engineers, but also many other researches and scientists face to many difficulties in solving a related constraint optimization problem. Therefore, o many miscellaneous techniques applicable on all or limited type of problems have been developed until now. Coello [15] and Montes and Coello [16] both are comprehensive review surveys on different constraint handling techniques. Typically, three main groups of constraint handling techniques are available in literatures:

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a) penalty-based techniques, b) modified Evolutionary Algorithms (EAs) or hybrid algorithms such as Co-Evolutionary Algorithms (CoEAs) and c) miscellaneous techniques.

The most well-known methods are penalty techniques that have different forms such as static penalties, dynamic penalties, death penalty, adaptive penalty and so on, but logically similar in strategy for handling constraints. Some other researchers have focused on the manipulated versions of the algorithms to directly embed a constraints-handling technique into the logic of the algorithm. Yousefi et al. [17] have improved ICA with a feasibility-based ranking embedded algorithm applied for handling design constraints of heat-transferring plates. Nema et al. [18] have presented a hybrid co-evolutionary version of PSO combined with the gradient search and used an augmented Lagrangian method as the handling constraints technique. Mun and Cho [19] explained a modified HS algorithm with an embedded Fitness Priority-Based Ranking Method (FPBRM) to handle design constraints. Zade et al. [20] introduced a hybridized cuckoo search with box-complex method to not only handle design constraints but also increase the convergence rate and computation facilities. Mendez and Coello [21] utilized a selection mechanism and incorporated it into a DE algorithm to handle constraints. Liu et al. [22] presented a modified PSO using a Subset Constrained Boundary Narrower (SCBN) method cooperating with a Sequential Quadratic Programming for finding near-boundary feasible answers for solving engineering problems. Lee and Kang [23] is a work on handling constraints in water resources optimization problems with modifying an EA called Shuffled Complex Evolution (SCE) with an adaptive penalty. Stripinis et al. [24] presented a constraint handling technique with incorporating a two-step selection procedure and a penalty function called the direct type constraint handling technique. These algorithms, although efficient and useful, usually sophisticated in logic or need exhausting programming and might not be simply available for users.

Other miscellaneous ideas are available among literatures, as well; Chehouri et al. [25] presented a method, so-called Violation Constraint Handling (VCH) technique for GAs by utilizing a violation factor without tunable parameters and displayed a consistent behavior in the results. Guan et al. [26] have developed a repairing procedure added on GAs for handling constraints with application on water resources optimization problems. Mallipeddi and Suganthan [27] utilized four different constraint handling technique, Superiority of Feasible Solutions (SF), Self-Adaptive Penalty (SP), ε-Constraint (EC) and Stochastic Ranking (SR) simultaneously cooperating with each other according to some outlined rules and called it Ensemble of Constraint Handling Techniques (ECHT) which outperforms all of the four techniques when utilized individually. Leguizamón and Coello [28] developed a boundary-search constraint handling technique utilizing two local and global level exploration, based on an Ant Colony Metaphor.

Moreover, a few papers have focused on optimizing skeletal structures. For example, Kaveh and Zolghadr [29] have applied a penalty function to handle natural frequency constraints on some small/mean scale strucutres. Their algorithm has beaten all other former literature. The other one exterior penalty function utilized by Gholizadeh and Barzegar[30], is a technique that sequentially provides unconstrained situation for handling natural frequency constraints. Also, the method presented in Kim et al. [31] is an improved version of PSO that simply makes the problem unconstrained. Pholdee and Bureerat [32] has compared the results of a fuzzy-set penalty function by Cheng and Li [33] and three aforementioned techniques. In the other work by the same authors (i.e. Bureerat and Pholdee [34]), they have introduced a more powerful penalty that outperforms Ref. [29]. Their new penalty function, shows best standard deviation among all former techniques while the mean, max and min of the statistical study are in the scope of others.

All the above-mentioned concepts are undoubtedly excellent works but they are not simply available and mostly not specific for structural design problems; the scholars of these studies have not utilized structural design point of view and mostly they have had a heuristic and/or artificial intelligence-based inspiration for their developed techniques. In the other words, such techniques manipulate exploration/exploitation in optimization process and do not use the fitness function by inspirations from routines and logics of specific properties of the studied problem, (the structural design optimization problem in this paper). Moreover, all aforementioned techniques have no statistical evidence about reliable stable performance on large scale structural design problems. As the final deficiency, due to general vision behind developing such techniques and no-specific-problem based nature, when the search space re-shapes from one problem to another, those techniques obviously need some parameters to be adjusted from one optimization problem to another one and accordingly, this forces the user to start trial-and-error for to fulfill aim. It should be noted that with current computation possibilities, such trial-and-error processes take hours or even days and doing such attempts depict an inconvenient atmosphere for the user in starting step of the structural optimization. Hasançebi and Erbatur [35] have tried to avoid tunable parameters of an old penalty technique and eliminate its shortcomings for providing an improved performance with a reformulation; but again, designing view is not considered due to basic vision in their research.

2 Motivation Behind Providing A New Constraints-Handling Method

Lack of a Design-Vision based technique specified for the structural optimization, motivated the authors to provide a new reliable constraint handling technique. In the first look, one may simply believe that providing a deal with computational cost of the optimization process might be a better way than a fitness-based technique to facilitate trial-and-error attempts; but available works on improving computation efficiency from spotlight scholars show that computation expedition methods are not in a level to highly facilitate such attempts in a way to easily make the process convenient and user friendly. Here are some examples: Kaveh and Talatahari [36] presented an improved ACO utilizing Sub-Optimization Mechanism (SOM) to reduce the size of pheromone vector, decision vector, search space and number of fitness evaluation to expedite optimization process. Hasançebi [37] is an attempt to improve computational performance of adaptive evolution strategies and also increase efficiency of algorithm with an adaptive penalty function. Azad et al. [38], Azad and Hasançebi [39], Azad et al. [40] and Hasançebi and Azad [41], all are struggles for improving the efficiency of various algorithms for solving large scale structures applying an outstanding strategy called Upper Bound Strategy (UBS). Also, Azad and Hasançebi [42] is an attempt to use a Guided Stochastic Search (GSS) technique which is based on the principle of virtual work to enhance computational efficiency. Kambampati et al. [43] present a sparse hierarchical data structure called Volumetric Dynamic Grid (VDG) in combination with Fast Sweeping Method and multi-threaded algorithm for faster convergence in topology optimization of structures by Level Set Method (LSM). The work by Dunning et al. [44] is an attempt to overcome with computationally difficult and expensive eigenmodes of buckling constraints with reuse of current available eigen vectors, optimal shift estimates and some other ideas to effectively overcome with a large number of buckling modes in topology optimization. Duarte et al. [45] and Sanders et al. [46], both introduce two versions of an efficient software for computationally fast analysis of polygonal finite element meshes with many degrees of freedom. With an investigation on these references, it is clear that such expeditions do not eliminate boring tuning situations. Not only that, but in Venkataraman and Haftka [47], it is illustrated that optimization complexity grows as the computations' possibilities improve and eliminating such costs would be more and more hard and out of reach. Thus, seemingly the only way would be eliminating the tuning necessity with a strategy that basically does not require tuning. In current techniques main reason of tuning is that search space is re-shaped when shifting among different optimization problems.

To sum up, to propose a technique not-general for all optimization problems but specific for structural design, it is necessary to find some properties that does not change from one structure to another. Therefore, three major initial outlines are summarized as:

1) The new formulation should utilize a property that is true for all structural search spaces (to eliminate tuning necessity); To fulfill this aim, the fuzzy feature of structural search space is utilized in this paper.
2) The new method should have design-based idea that applies for all the structures to generalize the method for the structural optimization; here, the Ideal-Design strategy is presented.
3) The formula should guarantee the searching quality to help algorithm/s in finding proper solutions.

Those three major properties will be completely general among structure. With adhering those outlines, the proposed method will:

1) not focus on penalty techniques or parameter tuning basically (no trial-error attempts needed),
2) not manipulate algorithms by complex add-on ideas and simple version algorithms can be good enough to dive into optimization process, right away,
3) not focus on computational efficiency improvements, either software improvements or hardware boosting.
4) not need sophisticated programming and can be simply established for all structures.

3 Background

3.1 Conventional Structural Optimization Formulation

Optimization, from the mathematical point of view, contains to find extremums; namely minimum or maximum results. In this paper, for matching with the structural weight-based optimizing, the minimization problem should be considered. The basic statement of a minimization problem involves an objective function and some constraints, as:

$$\begin{gathered} Find\ \vec{X} = [x_1, x_2, x_3, \dots, x_{nv}] \\ To\ minimize\ \ F(X) \end{gathered} \tag{1}$$

$$Subject\ to\quad x_{iv} \epsilon D\ ,\ iv\ =\ 1,2,\dots,nv$$

$$g_j(X)\ \leq\ 0\quad j = 1,\dots,nc$$

where, $F(X)$ is the objective function, x_{iv} are problem variables, nv is the number of variables, X is the vector of variables, D is the acceptable domain and $g_j(X)$ is the j_{th} constraint of the problem. In a minimization problem, the goal is to find a solution X_i to minimize $F(X_i)$, which must satisfy the constraints that are expressed in the inequality form $g_j(X)\ \leq 0$. For structural optimization problems, the weight of the structure, W, conventionally has been the objective function. Design criteria such as capacity controls for members, inter-story drifts, stability, strength and so on from famous design codes such as AISC [48] have formed the constraints for the structural optimization problem. In addition, cross section of members, A, are usually design variables. Therefore, the conventional form of structural optimization problem is as:

$$Find\quad A\ =\ [A_1,\ A_2,\dots,A_n] \tag{2}$$

To minimize W(A)

Subject to: Design Criteria

Handling constraints is a significant difficulty in constrained problems. In a minimization problem, the main strategy is to add an extra value to the solutions that violate some constraints. In other words, this constraint-handling technique produces another value instead of objective value (i.e. $Fitness\ (X_i)$ instead of $F\ (X_i)$) for the available solution (X_i) that brightens the difference of feasible and infeasible solutions to the algorithm. So, the fitness value is a function of the objective and constraints. This means that although an infeasible solution may have a smaller $F\ (X_i)$, it will have a higher fitness. For forming such fitness functions, different approaches are developed yet; however, the focus of the following sections is on providing a new powerful fitness function specified for structures.

3.2 Fuzzy Set Theory and Structures

It can be shown that structural search space has a less-known fuzzy feature; therefore, we decided to use this general feature to handle design criteria. In the following, a brief review on fuzzy set theory and its conformity with structural search space are presented. Then, a fuzzified fitness is proposed based on three basic outlines mentioned before.

For the first time, Zadeh [49] presented the idea for fuzzy point of view to truth-check reactions. He developed the proposal of "fuzzy-set" theory immediately after defining "fuzzy logic"; and argued that the truth-check could have an uncertain reaction. In other words, unlike common binary logic (or so-called Boolean logic) that reacted to a logical situation with distinct reactions (such as 0 or 1, ok or not-ok, yes or no, black or white and so on), such logic has a non-distinct point of view. That is, the reaction against a logical situation could be a mixed reaction. For example, a logical check might be evaluated somehow ok and somehow not-ok or somehow yes and somehow no and everything like that. The term fuzzy represents situations, which are obscure or have a sense of uncertainty. As a simple example, honesty epithet could be obscure; somebody might be extremely honest, usually honest, usually dishonest and extremely dishonest. Then, the reaction against the questioning one's honesty would not be distinct. Fuzzy set predicates to a set with members that all follow such logic from an epithet point of view. One advantage of fuzzy point of view is that setting a fuzzy-membership value to all the members would be rewarding to distinguish them from each other. A remarkable example would be a flock of sheep with black and white color on skin. The reaction against questioning the color of a single sheep is not distinct. The sheep are somehow white and somehow black. Black and white are indexes for color epithet and there are Index Portions (IP in brevity) for both black and white on the skin of any sheep. To dedicate fuzzy membership-value for a sheep, the portion of white color (IP_{White}) and black color (IP_{Black}) on the skin would help to provide a formula like:

$$\begin{gathered} Membership\ function = \overbrace{IP_{Black} \times Black}^{A} + \overbrace{IP_{White} \times White}^{B}, \\ IP_{White} + IP_{Black} = 100 \end{gathered} \tag{3}$$

In Eq. (3), term A is the fuzzy value for black color and term B is the fuzzy value for white color. If the considered epithet had quantitative indexes, unlike black and white, the membership function can produce a numerical value for all the members of the fuzzy set (i.e. flock). It will be shown that the same situation governs structural search space, as well.

When structural engineers try to design a structure, they confront with selections that some of the members or stories have satisfied design criteria and some others have violated them as controlled by using a famous design software such as ETABS. A look at Figs. 1 and 2 could be rewarding. Fig.1 is a familiar depiction for engineers after analysis/design where some elements have satisfied design capacity checks and some others have not. Also, Fig. 2 shows a schematic inter-story drift check that the third and fourth stories have Drift Indexes (DI in brevity) greater than 1 (violated), while the second story has a DI equal to 1 and the first story has a value less than 1. Such designs are somehow feasible and somehow infeasible, the feasibility of a design is the target epithet and reaction against questioning the feasibility of such design is not distinct. This means that in order to be able to distinguish a good (feasible) or bad (infeasible) design, using a fuzzy membership function is possibly efficient. Accordingly, by defining a fuzzy membership function for structural designs, a representative fuzzy membership value for all designs are accessible.

Often normal forms of design criteria such as capacity and/or inter-story drifts are indexes for feasibility/infeasibility of an element or a group of elements. Some of the design criteria are directly stated in the normalized version in famous design codes while others need to be re-written in normalized form and then used in our formulations. For example, strength criteria of an element are presented as following in AISC [48]:

$$\begin{gathered} Capacity\ Ind = \begin{cases} \dfrac{Pu}{2\varphi cPn} + \dfrac{Mux}{\varphi bMnx} + \dfrac{Muy}{\varphi bMny} & For\ \dfrac{Pu}{\varphi cPn} < 0.2 \\ \dfrac{Pu}{\varphi cPn} + \dfrac{8}{9}\left(\dfrac{Mux}{\varphi bMnx} + \dfrac{Muy}{\varphi bMny}\right) & For\ \dfrac{Pu}{\varphi cPn} \geq 0.2 \end{cases} \\ \rightarrow Capacity\ Index \leq 1 \end{gathered} \tag{4}$$

(a)	(b)	(c)	(d)

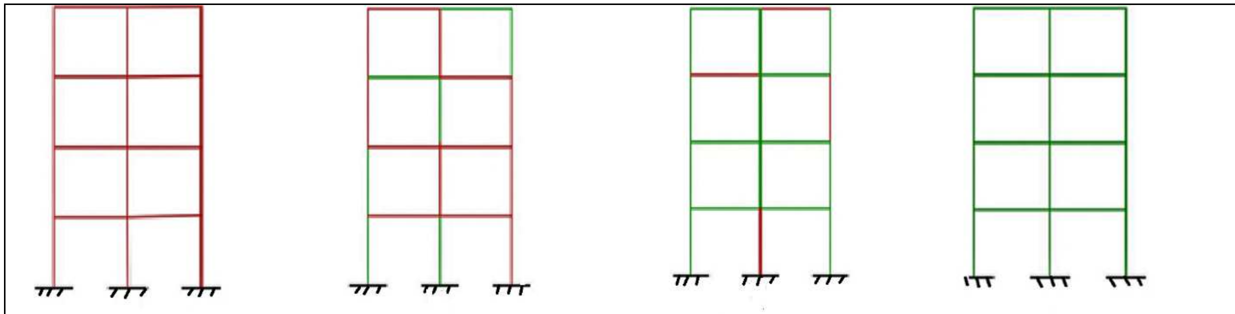

Fig.1 A schematic of structures with violated/satisfied capacity index (red: infeasible, green: feasible); (a) structure is completely infeasible; (b) and (c) structures are semi-feasible; (d) structure is completely feasible.

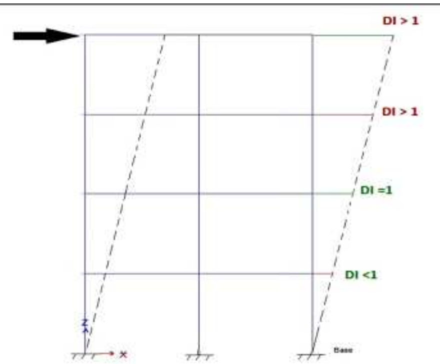

Fig. 2 A schematic of structures with violated/satisfied drift index

where, Pu is strength demand; Pn is the nominal axial strength capacity; Mux and Muy are flexural strength demand in the x and y directions, respectively; Mny and Mnx are nominal flexural strength capacities. Φc is resistance factor ($\Phi c = 0.9$ for tension and $\Phi c = 0.85$ for compression); and Φb is the flexural resistance reduction factor ($\Phi c = 0.9$). Eq. (4) calculates section Capacity Index (CI) according to AISC [48], and states that index must be equal or less than one. Casually, AISC [48] directly introduces this index to be compared with one and does not need to be normalized; all required forces, namely Pu, Mux and Muy are normalized with their allowable values φcPn, $\varphi bMnx$ and $\varphi bMny$, respectively. Therefore, we directly can use this formula as normalized $Capacity\ Index\ (CI)$ in our formulation. However, for inter-story drift criterion, the situation is different. The related equation in codes is as:

$$\frac{d_s}{h_s} \leq R_I\,, \qquad s = 1,2,\ldots,ns \tag{5}$$

where, d_s is the inter-story drift of sth floor, h_s is the height of sth story. Eq. (5) illustrates that story drift must be less than a pre-defined value R_I (it is set to $1/400$, in this work), but we need a normalized version so re-write it as:

$$Drift\ Index = \frac{d_s/h_s}{R_I} \leq 1 \ \rightarrow\ Drift\ Index\ \leq 1 \tag{6}$$

Eq. (6) provides an appropriate equation in which the left side would be compared with one. Therefore, we selected it as usable $Drift\ Index\ (DI)$.

4 Presenting New Formulation for Structural Optimization Problems

After detecting the possibility of assigning a fuzzy membership for any design, we thought about the mechanical basis for composing such membership functions in a way to help optimizers to find the lightest feasible designs. Therefore, two levels of designing are offered: a) Element-wise section idealizing level and b) Feasibility-saving level.

a) Element-wise section idealizing level: Initially, we will explain about how a single element could be an ideal one and compose it in form of a fuzzy-membership/fitness function. A free-body diagram of an element is shown in Fig. 3. $C_i = \{CI_i, DI_i\}$ is considered as the set of normalized design constraints for i_{th} element. The best feasible design for i_{th} member should have the lowest possible area of the cross section with the highest possible strength and stiffness (i.e. moment of inertia); while when the area of cross-section Ai (and simultaneously weight of the element) decreases, its maximum possible strength and stiffness often decrease, as well. This means that an ideal feasible element, with mechanically weakest and lightest possible section, would have at least one of indices (i.e. CI or DI) should be equal to one (i.e. situations A, B or C in Fig. 3). A simple function for fuzzifying the constraints C_i for i_{th} element could be as:

$$f_1(x) = \begin{cases} (x-1)^2 & x \leq 1 \\ x & x > 1 \end{cases} \tag{7}$$

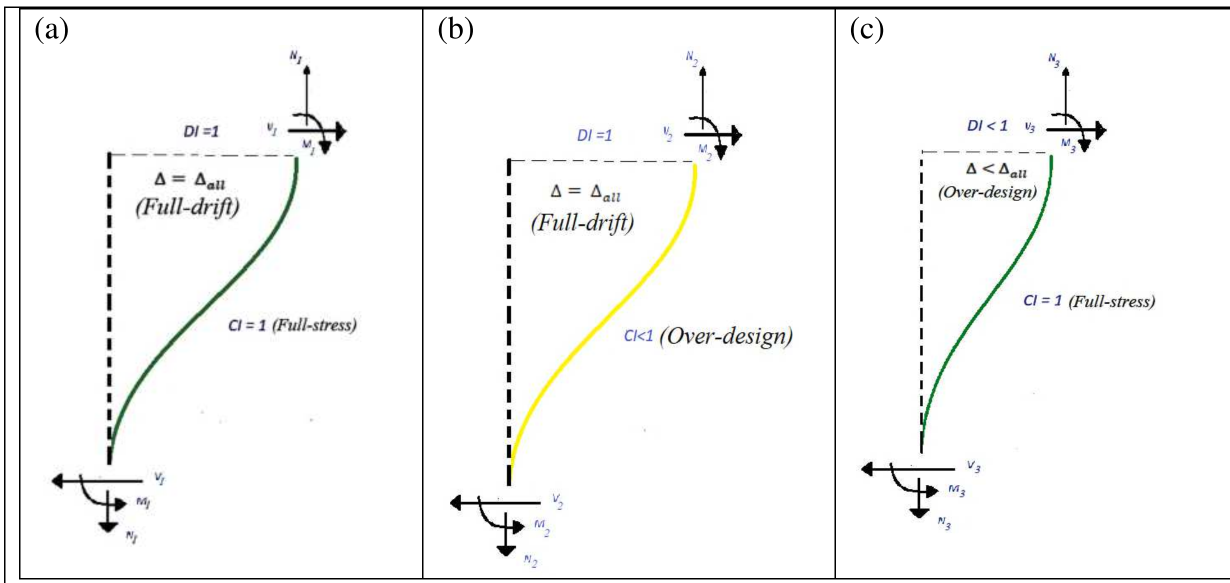

Fig. 3 An ideal free body-diagram of an element; at least one of the indexes would be equal to zero if the search domain is continuous; (a), (b) and (c) all are considered as ideal designs in this paper.

The reason that such rule was chosen for f_1 might be clarified regarding Fig.4. Since for acceptable values of x, namely $x \leq 1$, and taking into account that $0 \leq |x-1| < 1$, (x would be a representative of normalized indexes C_i), it is preferable to give a lower value for $x \leq 1$ rather to $x > 1$ to boost exploration among acceptable elements; therefore with using the power of 2, as $x \to 1^-$, $f_1 = |x-1|^2$ tends to 0 faster than $f_1 = |x-1|$. Apparently, $maxC_i$ is an appropriate representative for C_i since when $maxC_i > 1$, the element is not acceptable and if $maxC_i \leq 1$, the element is acceptable. Then, we modify Eq. (7) substituting x by $maxC_i$ as

$$f_1(maxC_i) = \begin{cases} (maxC_i - 1)^2 & maxC_i \leq 1 \\ maxC_i & maxC_i > 1 \end{cases} \quad (8)$$

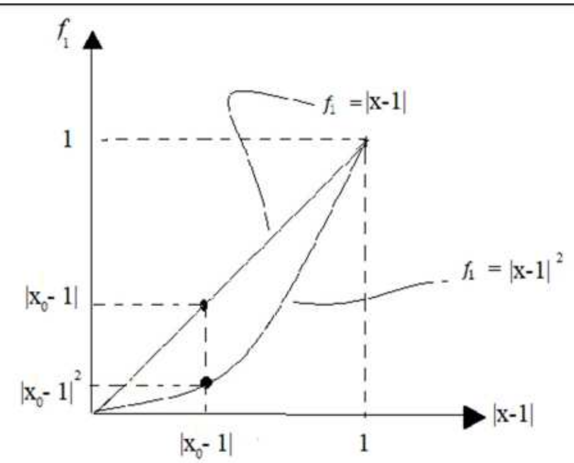

Fig. 4 The f_1 function

Authors decided to consider the portion for each element, story or group of elements in fuzzy function $(F_1)_i$ equal to its normalized weight to the total weight of the structure; then

$$p_i = w_i / W \quad (9)$$

where, w_i is the weight of i_{th} element and W is the total weight of the structure. So, the fuzzified sub-values of elements would be as:

$$(F_1)_i = p_i \times f_1(maxC_i) = \frac{w_i}{W} \times f_1(maxC_i) \quad (10)$$

and the final fuzzy value for the structural elements would be simply the summation of those values for all the elements, as:

$$F_1 = \sum_{i=1}^{nm} (F_1)_i = \sum_{i=1}^{nm} \frac{w_i}{W} \times f_1(maxC_i) \quad (11)$$

where, F_1 is the fuzzy membership function for the elements of the structure. In this function, the viewpoint behind F_1 is to design each element independently without regarding it as a member of whole structure by trying to minimize this value and in this way, utilized algorithms will logically try to find the ideal design for the all members of the structure one-by-one by tending all the terms in the formula to zero; In F_1, the effect of absolute value for the weight of each element w_i is eliminated due to normalizing with the total weight of the structure; in other words, the portion vector for fuzzifying the formula is

$$\vec{p} = (p_1, p_2, \dots, p_{nm}) = \left(\frac{w_1}{W}, \frac{w_2}{W}, \dots, \frac{w_{nm}}{W}\right), \quad (p_i \neq 0) < 1 \ \Lambda \ \sum_{i=0}^{nm} p_i = 1 \ , \quad (12)$$

This feature means $\vec{p}$ is always a normal vector not equal to zero and numerically plays no role in making F_1 equal to zero; and the algorithm will persistently try to idealize all the elements, namely trying to satisfying the following expression:

$$\overrightarrow{f_1} = \left(f_1(C_1), f_1(C_2), \ldots f_1(C_{nm})\right) = \overbrace{(0, 0, \ldots\ldots, 0)}^{nm\ count\ of\ zeros} \tag{13}$$

and consequently, for the vector of constraints $\vec{C}$, we have:

$$\vec{C} = (maxC_1, maxC_2, \ldots\ldots, maxC_{nm}) = \overbrace{(1, 1, \ldots\ldots, 1)}^{nm\ count\ of\ ones} \tag{14}$$

In the first look, it seems that this is really efficient for finding lightest feasible design since the optimization algorithm will finally find all ideal elements; however, we may need a deeper look. Fig. 5 shows a schematic depiction of different designs in the search space; X_i is the possible design and the vertical axes shows the weight of the structure, $W(X_i)$; for simplicity, there are just three normalized design indices depicted in the Fig. 5 denoted by I_1, I_2 and I_3. Nine yellow points are chosen to be investigation carefully. Points 1 and 2, both are the intersections of the three indices and both completely-feasible, but point 2 is lighter. Points 3, 4 and 5 are intersection of just 2 of 3 indices; points 3 and 5 are feasible, but point 4 is infeasible. Point 6 is semi-infeasible; point 7 is a feasible point, located on I_3. Point 8 is completely feasible, but it is an over-design point. Point 9 is completely infeasible and is an under-design point. Such imagination advocates that the behavior of whole structure is complicated than behavior of a single element. Now there would be three basic important questions:

1) Is there any common intersection among all indices so that the situation in Eq. (14) happens and all the elements are ideal?
2) If such point is available, does it correspond to the exact global lightest feasible design?
3) If the answers of those questions are negative, then what would be the $\vec{C}$ vector for the exact global lightest feasible design?

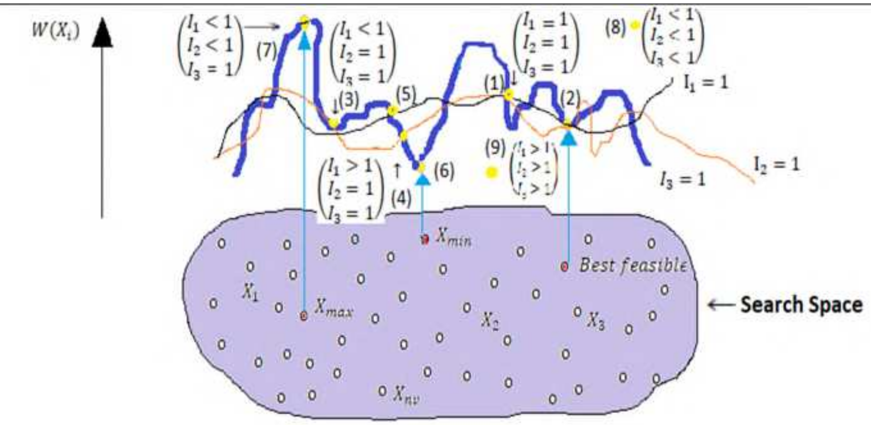

Fig. 5 A schematic point of search space, X_i, with equivalent weight, $W(X_i)$, three colored lines are some constraints according to indexes I_1, I_2 and I_3. Eight yellow points show different possible situation of the three indices.

Actually, the authors did not find any literature discussing on the possible answers of those questions and discussing them is out of the scope of this paper; but, openly, in the worst situation, namely, when the situation in Eq. (14) does not exist, or exists but does not correspond to the lightest feasible design, we can simply conclude that the $\vec{C}$ vector of the global lightest feasible design has at least one element less than one; therefore, we decided to provide the possibility of saving feasibility during exploration so that the idealization of the elements continues until the feasibility is saved. In other words, idealizing elements without saving feasibility of the search may lead to points like 4, 6 or even casually point 9. This is because of two reasons: first) meta-heuristic algorithms are global search algorithms and random selection is an intrinsic property of such algorithms and there is a necessity in the fitness formula to take-back exploration from infeasible spaces on the search space if such spaces casually happen; second) there is no warranty that F_1 value for one completely-feasible and semi-feasible structure is different and worst design may have lower F_1 value. For this purpose, in the following, we present another fuzzy function called F_2. Unlike F_1, the new function will evaluate the feasibility of the whole structure.

b) Feasibility-saving level: Considering the presented matters, the new fuzzifying function is presented as:

$$f_2(n_f, n_{inf}) = \begin{cases} n_f w_f & , \quad n = n_f \\ n_{inf} w_{inf} & , \quad n = n_{inf} \end{cases} \tag{15}$$

where, n_f and n_{inf} are number of feasible and infeasible elements, which are the indices of feasibility and infeasibility, respectively; $n_f + n_{inf} = nm$, and w_f and w_{inf} are cumulative weights of the feasible and infeasible members of the structure, respectively; while $w_f + w_{inf} = W$. As far as we know, the main concern of using a fitness function in an optimization process is to provide representative parameters to evaluate level of its feasibility (feasibility ratio). On the other hand, we need to have the effect of weight as the other main parameter (economical point of view). Seemingly, this set of parameters provides a good potential choice to reach all of these objectives. However, this was just a proposed group of variables by our team and future works around the topic may have other suggestions. According to the main goal, the infeasible part of the structure must tend to zero during optimization to find feasible structures; mathematically stated as:

$$\lim_{\substack{Optimization \\ \to feasible\ point}} \frac{n_{inf} w_{inf}}{n_f w_f} = 0 \tag{16}$$

The fraction in Eq. (16) is a fuzzy fraction for any structure (with a minimum equal to 0 so its minimization makes sense); but for formulation purposes, a reasonable equivalent to this fraction is replaced as:

$$1 + \lim_{\substack{Optimization \\ \to feasible\ point}} \frac{n_{inf} w_{inf}}{n_f w_f} = \lim_{\substack{Optimization \\ \to feasible\ point}} \frac{n_f w_f + n_{inf} w_{inf}}{n_f w_f} = 1 \tag{17}$$

Although the expression $n_f w_f + n_{inf} w_{inf}$ is not quantitatively equal to $nm \times W$ but as the numerical point of view they are logically peer valued:

$$\frac{n_f w_f + n_{inf} w_{inf}}{n_f w_f} \propto \frac{nmW}{n_f w_f} \tag{18}$$

then we have:

$$\lim_{\substack{Optimization \\ \to feasible\ point}} \frac{n_f w_f + n_{inf} w_{inf}}{n_f w_f} = \lim_{\substack{Optimization \\ \to feasible\ point}} \frac{nmW}{n_f w_f} = 1 \qquad (19)$$

Eq. (19) is selected as the feasibility-saving level fuzzy membership function, F_2 (which has a minimum on 1 so its minimization makes sense):

$$F_2 = \frac{nmW}{n_f w_f} \qquad (20)$$

Finally, the summation of F_1 and F_2 is the simplest way to combine these to levels of fuzzy-membership/fitness functions. Then we have:

$$Fuzzy\_membership = F_2 + F_1 = \frac{\frac{W}{w_f}}{\frac{n_f}{nm}} + \sum_{i=1}^{nm} \frac{w_i}{W} \times f_1(maxC_i) \qquad (21)$$

Traditionally, in the optimum design literatures, the members of provided design examples are grouped (e.g. for fabrication facilitation) and sectional updates during optimization applies on the groups. For consistency with literature, we shift indices of Eq. (21) to groups of the structure and re-write it as:

$$Fuzzy\_membership = F_2 + F_1 = \frac{\frac{W}{w_{fG}}}{\frac{n_{fG}}{nG}} + \sum_{i=1}^{nG} \frac{w_i}{W} \times f_1(maxC_i) \qquad (22)$$

where, nG is the number of the groups in structure; n_{fG} is the number of feasible groups and w_{fG} is the cumulative weight of feasible groups. By using this formula as the fitness function, algorithms can save the feasibility during exploration and idealize the groups of the elements in the structure, simultaneously:

$$\lim_{\substack{Optimization \\ \to Ideal\ Feasible\ Point}} (Fuzzy\ Fitness) = \lim_{\substack{Optimization \\ \to Ideal\ Feasible\ Point}} (F_2 + F_1) = 1 + 0 = 1 \qquad (23)$$

In Eq. (23), F_2 receives absolute 1 when the found design is feasible; F_1 receives absolute 0 when the whole found sections are ideal ones. Therefore, $F_2 + F_1$ receives an absolute 1 when the Ideal feasible design is found (and its minimum is 1). In truss structures, assigned cross section values are continuous, unlike moment frames. Accordingly, truss structures optimization has chance to provide a whole structure with ideal feasible elements, say $F_1 = 0$. In frames, although not impossible, it seems to be rare.

Two points should be clarified regarding the FIFD technique:

-First, although the proposed idea utilizes some difficult concepts of structural properties and fuzzy logic, however it is very simple for implementing. This method just needs the weight of elements and the value of design constraints. These values are the base for almost all other methods. To simplify the present method, we use the normalized format of these values. As a result, this method does not impose further computation costs.

-Second, since meta-heuristics converge to a vicinity of global optima and not exactly to the global optima itself, any necessity for our membership to have the exact global optima same as the original optimization was eliminated. Therefore, the only main thought was to propose a formulation that its minimization gives opportunity to meta heuristic algorithms to meet lighter feasible answers. This way, we omitted any struggle for analytic proves. In other words, we logically can prove that the total trend of minimizing F_1 is equivalent to total trend of minimizing structural total weight W because of one strong logic: large scale reduction in the total weight of a heavy feasible structure will mostly push normal values of constraints towards 1 or further and for very light feasible answers, simultaneous small values for w_i and $1 - C_i$ terms in F_1 (for $C_i \leq 1$) will take place and F_1 will reduce intensively. Also, since F_1 by itself does not remove the possibility of meeting infeasible answers, F_2 accompanies F_1 to save feasibility of exploration and supply more feasible answers to be assessed by F_1. In other words, minimization of Fuzzy-membership is not fully correlated with weight minimization, but absolutely small membership values (i.e. minimums of membership) belong to very light feasible answers which are the target dream-like designs. We have observed the correctness of this logic through the brilliant reported numerical results.

5 Utilized Methods

5.1 Optimization methods

To verify that the FIFD technique fully adapts with different meta-heuristics and the results are stable and reliable, several algorithms are selected to be utilized in this paper such as: GA[1], ACO[5], PSO[3], CSS, Interior search algorithm (ICA)[9], Firefly Algorithm (FA) [50-51], Symbiotic Organisms Search (SOS)[52], Upgraded Whale Optimization Algorithm (WOA)[53], Interior Search Algorithm (ISA)[54]. The constant parameters of these algorithms are set as the same as the standard versions provided by the main references as presented in Table 1. In order to have statistical outputs, 30 optimization runs were performed by each algorithm.

Table 1. Parameter summary of the alternative metaheuristic algorithms.

5.2 Utilized penalty techniques

The list of all penalty methods applied to the examples is summarized in Table 2. For the first and second examples, to show the adaptability of FIFD with different algorithms, the results of optimization by FIFD are achieved by penalty of Ref. [57].

Table 2 Different utilized penalty methods; all the formulas are extracted from Coello [15]

6 Numerical Examples and Results

This section presents the details of frame structures as well as the numerical results of optimization obtained by different methods. AISC [48] and ASCE [55] are the codes for designing and loading of the examples, respectively. In addition, aforementioned normalized design constraints, the CI and DI are selected as criteria.

The proposed technique is tested on three frames optimization; 10-story frame, X-braced 20-story tall frame and 60-story mega-braced tubed frame. First and second frames, both are benchmark examples in literature. The possible sections for structural members of examples were taken to be of 268 W-shaped standard profiles. Properties of utilized steel material were $\rho = 7850\ Kg/m^3$, $E = 200\ GPa$ and $F_y = 248.2\ MPa$, as the mass density, modulus of elasticity and yielding stress, respectively. 10-story and 20-story frames are loaded by dead, live and seismic loads while the tubed frame is loaded by dead, live and wind loads due to its high-rise nature. In the following, each example is described and numerical results are presented afterwards.

6.1 10-story frame

This model, as the first example, is shown in Fig. 6 and was firstly introduced by Azad et al. [38]. This frame contains 1026 elements, 580 beams, 350 columns and 26 X-type braces. The braces are applied just along x-axes for all bays in the first story and the side-bays of the other stories. Joints are moment resisting connections for beams and columns and pin connections for braces. 32 different groups of members are available and they are repeated in every three stories from 2nd story toward upwards; 5 column groups, 2 groups for outer and inner beams and 1 for bracings are the considered groups. It is noteworthy that all the story-nodes modeled as rigid-diaphragms and 10 story-diaphragms modeled for this example. In addition, the effective length factor for buckling stability for columns, braces and the major bending of beams are all taken equal to one. However, for the bending over the weak bending plane of beams, namely the plane orthogonal to the floor layer, this factor is taken equal to 0.01 since the beams are fully braced by the floors. The loadings applied on the floors are equal to 20KN/m dead and 12KN/m live, respectively. Simultaneously, 15KN/m and 7KN/m are the dead and live loads applied on the roof story. In this paper, the self-weight of the story is considered in the effective story weight for calculating the related seismic lateral load and gets updated time to time while exploration moved on by algorithms. According to ASCE [55], the lateral seismic load results as

$$F_x = \frac{w_x {h_x}^k V}{\sum_{i=0}^{n} w_i {h_i}^k}\ ,\ \ V = 0.1W \qquad (24)$$

where, the w_x and h_s are the effective weight and height of the story s, respectively; k is a function of fundamental period of the structure; and F_s is the lateral seismic load assigned to the mass-center of the story s; for this example, the seismic base shear V was taken equal to 10 percentage of weight of the structure W (i.e. $V = 0.1W$). According to ASCE [55], the fundamental period of the structure, may be computed by

$$T = C_T {h_n}^{3/4} \qquad (25)$$

where, C_T is taken equal to 0.0853 and H is the height of the structure equal to 36.5 m in this example. According to this formula, fundamental period of this structure T, is equal to 1.267s. According to ASCE [55] guideline, the K factor for this value of fundamental period is equal to 1.38. Additionally, different load coefficients applied to 10 load combinations are considered for all the examples as presented in Table 3.

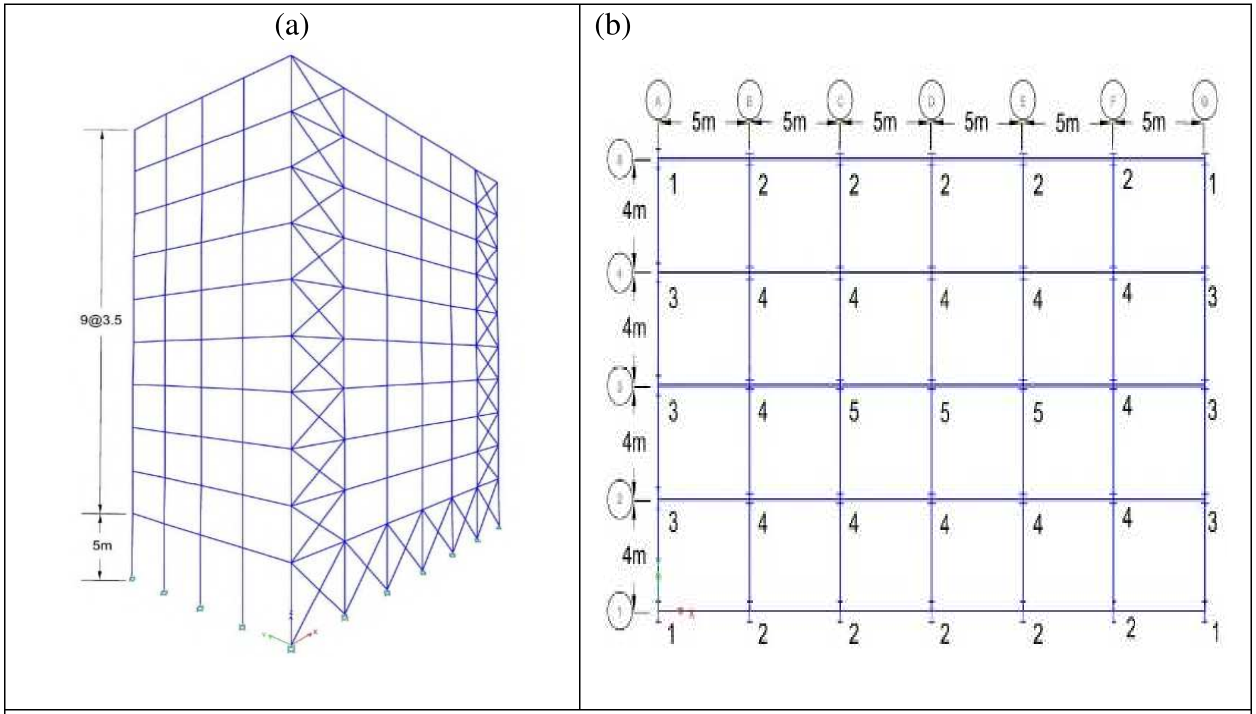

Fig.6 10-story 1026-element frame :(a) 3D view; (b) plan view and column groupings.

Table 3 Design load coefficients according to ASCE [55]

6.2 X-braced 20-story frame

This tall building consists of 8-bays in x direction and 6 bays in y direction; but the number of bays in x direction reduces to 6 from 7th story. Bays are 6m and 5m long, in x and y directions, respectively. The structure contains 3860 members; 1836 beams; 1064 columns and 960 bracing elements. This moment frame is braced with X-shaped braces in both x and y directions. In this frame, braces apply to frames one in a between; namely, grids 1,3,5 and 7 are braced parallel to x direction and grids b, d, f and h are braced parallel to y direction as shown in Fig. 7. Considering practical construction easiness, members divided into 73 groups, in every two stories; columns are divided into five groups, beams into two inner and outer groups and braces solely into one group as a whole for both stories. Effective length factor and unbraced length factor are exactly the same as the first example. This example was optimized by Azad et al. [40] applied gravity loads, dead and live loads, assigned as distributed loads on the beams of each floor. For the floors, 14 KN/m and 10 KN/m applied as dead load and live load, respectively; also, 12 KN/m and 7 KN/m applied on the roof story as dead and live loads, respectively. As a remainder, the self-weight of the structure is also added to the dead load.

Similar to the first example, the base shear is equal to 10 percent of effective weight of the structure; C_T is taken equal to 0.0488 and H is the height of the structure equal to 70 m for this example. The fundamental period of this structure, T, is equal to 1.181s and the K factor for this value of fundamental period is equal to 1.341. load combinations are the same as the first example.

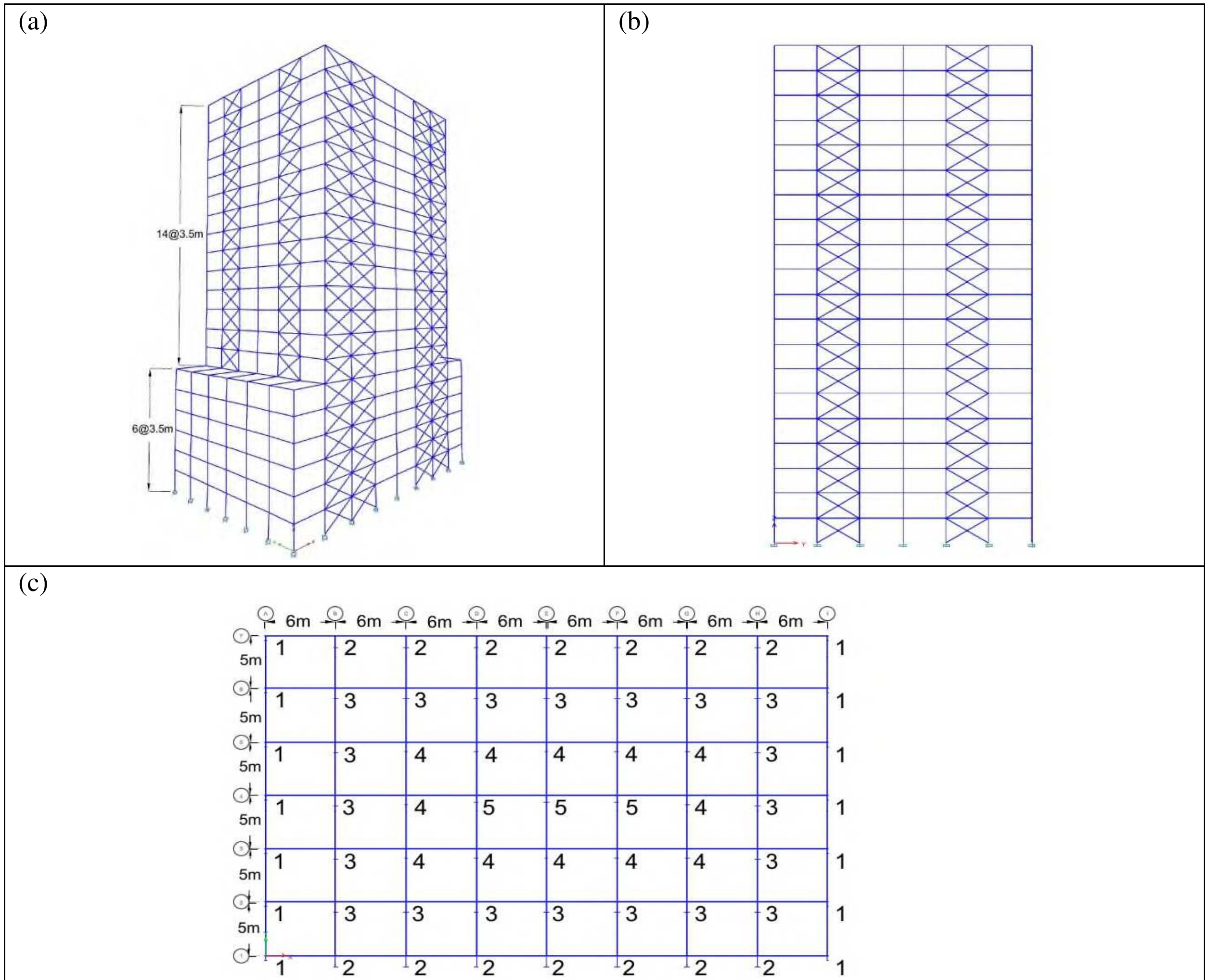

Fig7 20-story steel frame: (a) 3D view, (b) elevation views of frames B to H (c) the plan view and columns groupings

6.3 60-story Mega-braced tubed-frame

This high-rise building is made up of four rectangular independent tubed frames. As shown in Fig. 8, tube A has 4 bays in x direction and 2 bays in y direction; tube B, has 6 bays in x direction and 4 bays in y direction. Both tubes A and B continue to the top story. Tube C, has 8 bays in x direction and 6 bays in y direction and tube D has 10 bays in x direction and 8 bays in y direction in plan. The tubes C and D continue to story 42 and 24, respectively. The outer tube D, has mega-braces on each of its four elevation views, which are lozenge-shaped braces repeated every 6 story. As depicted in Fig8, every lozenge brace consists of 4 independent elements. However, tubes B and C have just bracings in the extreme right and extreme left bays at each of their four elevation views. This structure contains 8272 frame members contain 3960 beams, 3960 columns and 352 braces. It is noteworthy that tubes connect to each other by in-plane beam elements, hinged to the joints of the two tubes; therefore, the gravity loads of the floor system apply onto these elements. However, since the floor joints are diaphragm as a rigid body, these elements use determined sections and do not play any role in structural optimization and therefore excluded from structural members and optimization process. All the members are divided into 103 groups; each group covers every six succeeding stories; in plan of a story, any tube has its own beam group and columns are dedicated to the corner and side groups. Every 6 adjacent stories have their own bracing group, as well. Typical story height is equal to 3m for all the stories. Like former example, dead and live loads applied on story beams are equal to 14KN/m and 10KN/m, respectively; however, for roof story, these values are equal to 12KN/m and 7KN/m, respectively; because of high-rise nature of this structure, the wind load is supposed to be the major lateral load. According to ASCE [55], wind load may be computed as

$$P_w = (0.613 K_z K_{zt} K_d V^2 I)(G C_p) \qquad (26)$$

in which, P_w is the wind pressure on the structural surface in *KN/m*^{2}; *Kz* is the factor of velocity exposure; *Kzt* is the factor related to topography; *Kd* is the factor of winding direction; *V* is the wind speed; *G* denotes the gust factor and C_p denotes the external pressure coefficient. In this example, wind speed was set to 85 mph and exposure type to B; *Kzt* is set to 1, *Kd* equals to 0.85, and *G* is 0.85; *Cp* equals to 0.8 and 0.45 for windward and leeward faces of the building, respectively. Wind loads are considered as the major lateral loading.

6.4 Numerical Results and Discussions

6.4.1 Convergence results

Tables 4 and 5 present results for the 10-story frame, utilizing the FIFD and a penalty method to handle design criteria, respectively. All 9 algorithms with both constraint handling methods are used. The best weight among both tables is for the CSS algorithm as shown in Table 4 that is equal to 543.02(ton) found via applying the FIFD which is 8% lighter than the result reported in literature (i.e. in Azad et al. [38] equal to 584.93 (ton)) as mentioned in Table 5. Since some final results have some violation, to fairly compare, total weight is modified to present feasible weight as presented in Tables as practical weight. This means that we made some modification on final sections reported by the algorithm to exchange an infeasible result to a feasible one. Clearly, this modification is not necessary for feasible reported results. The reason is that final results handled by penalties in structural design optimization usually are not exactly feasible solutions as seen in our results. Thus, to gain an exact final feasible solution to be used in engineering practice, a handy manipulation in found final sections is necessary. This process usually results to an increase in the total weight of the structure. As seen in Table 5, five of nine reported solutions obtained by GA, CSS, ISA, SOS and WOA with the weight of 591.34, 549.24, 563.19, 549.51, 558.05 tons are infeasible and some modifications are needed upon their sections. Authors, after manipulating and gaining feasible solutions, reported new total weights as GA: 612.08 (tons), CSS: 561.13 (ton), ISA: 585.74(ton), SOS: 558.23 (ton), WOA: 569.55 (ton). All of the manipulated designs experienced an increase in the total weight with the minimum value of 2% for SOS and WOA and the maximum one of 4% for ISA. In addition to this, such manipulation is an excessive annoying process for designers. One superior feature demonstrated by the results in Table 4 is that, unlike the penalty methods, the FIFD converges to feasible solutions in almost all cases. It is interesting to see that all of the solutions in Table 4 are feasible ones and even some of them have DI equal or near to one (FA, ICA, CSS, ISA) which is the governing design criteria for this example. It means that FIFD precisely detects infeasibility and performs better than penalty over the boundary.

(a) (b)

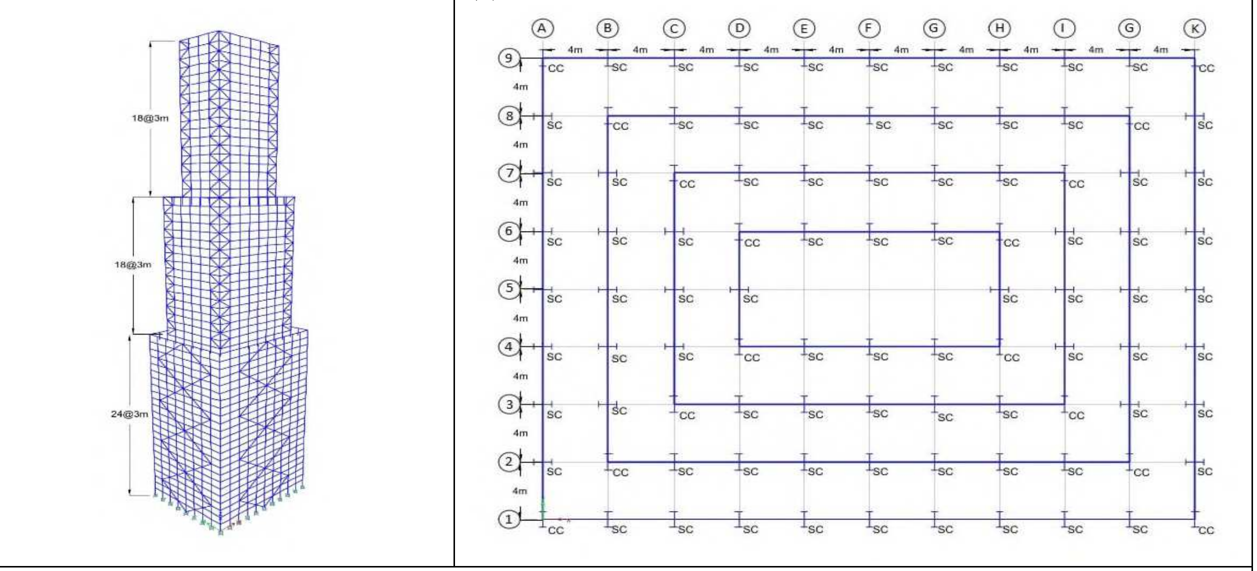

Fig.8 60-story tubed-frame: (a) 3D view, (b) the plan view for 24 initial story, (c) the plan view for stories 25 toward 42 and (d) the plan view for upper stories.

Table 4 10-story frame results; section properties, total weight of converged designs, maximum DI and CI, weights in practice resulted utilizing FIFD method along with 9 meta-heuristics

Table 5 10-story frame results; section properties, literature report, total weight of converged designs, maximum DI and CI, weights in practice resulted utilizing penalty along with 9 meta-heuristics

For the second example, Tables 6 and 7 present results for X-braced 20-story frame, utilizing the FIFD and a penalty mothed, respectively. Again, the best weight in both tables belongs to the CSS with a weight of 2713.57(tons) found via applying the FIFD which is much better than results obtained by the same algorithms advised by penalty methods and 24% lighter than the result mentioned by Azad and Hasançebi [42]. Again, all of the results of the FIFD are feasible solutions while many of the results of penalty-based method needed handy manipulation for practice purpose. The increase in the weight after modification is presented in the Table 7, as well. Like 10-story example, the FIFD shows its robust performance in discovering near/on the boundary solutions. Capacity, unlike 10-story example, is the governing design criteria and four of nine designs found by the FIFD are exactly on the boundary with CI near/equal to one.

Table 6 X-braced 20-story frame results; section properties, total weight of converged designs, maximum DI and CI, weights in practice resulted utilizing FIFD method along with 9 meta-heuristics

Table 7 X-braced 20-story frame results; section properties, literature report, total weight of converged designs, maximum DI and CI, weights in practice resulted utilizing penalty along with 9 meta-heuristics

Figs.10 and 11 are the convergence history of the best solutions found via the FIFD for the two examples. As it can be seen for the first example, after a minimum 13500 analysis all the algorithm show no more exploration while a minimum of 25000 analysis is required by most of chosen penalty techniques. Corresponding numbers for the second example are17500 and 25000, respectively. So, a tangible 46% and 30% reduction in the number of required analysis is achieved using the new developed technique for the first and second examples, respectively.

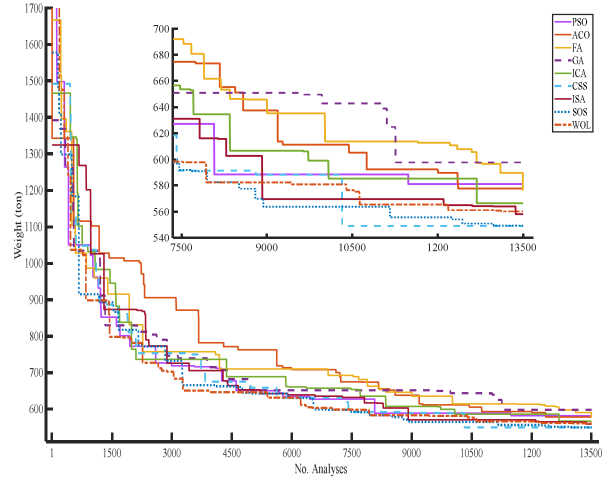

Fig.11 Convergence curvature of the best result of first frame (FIFD)

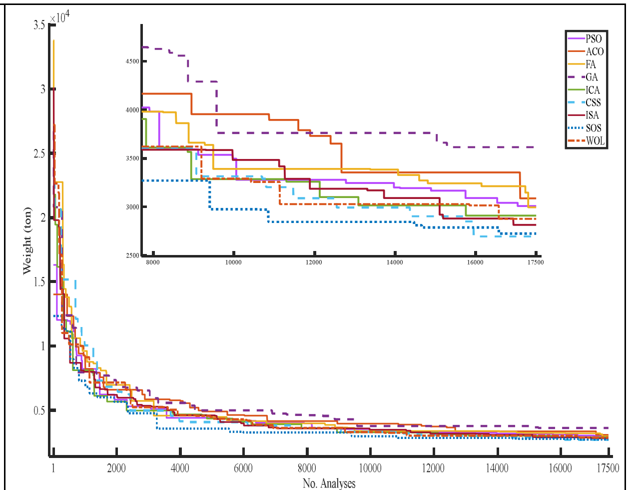

Fig.12 Convergence curvature of the best result of second frame (FIFD)

The best result obtained for first example by using the FIFD method belongs to the CSS and SOS algorithms that are 543.02 and 550.61(tons), respectively. ISA, WOA, ICA, FA, ACO, PSO and GA are placed the third to ninth levels that their weights are 559.32 (ton), 560.26 (ton), 568.48 (ton), 576.45 (ton), 578.96 (ton), 581.05 (ton), 598.27 (ton). The order for the results of the second example obtained by the FIFD are mostly the same as the first example: CSS, SOS, ISA, WOA, ICA, FA, PSO, ACO, GA, with the weights equal to 2713.57 (ton), 2775.39 (ton), 2817.29 (ton), 2921.28 (ton), 2913.79 (ton), 3036.29 (ton), 2993.51 (ton), 3112.13 (ton), 3614.55 (ton), respectively. This consistency can be interpreted as the stability of the performance when applying the FIFD. Considering random and heuristic nature of the utilized algorithms, total view to the order of performance of the algorithms illustrates a keen stable independent performance of the FIFD from search space deformation when shifting between different examples. However, the situation is completely opposite for the penalties and the order of the consequent weights is totally messy; for 10-story example, the order is as CSS, SOS, WOA, ISA, ICA, GA, PSO, ACO, FA; While for the 20-story frame, it is as CSS, SOS, ISA, WOA, PSO, FA, ICA, ACO, GA. This disarrangement shows that the utilized penalty in this research needs tuning to make sure a designer who utilizes only one algorithm for optimization. Penalty methods clearly fail to adapt shifting between the two examples.

The all-stories DIs of the first example for the results of three superior algorithms i.e. CSS, SOS and ISA are shown in Fig.11 which compares the FIFD and penalty methods final results obtained by these superior algorithms. As it can be seen, the distribution of displacement among stories of the results reported by the FIFD is smoother while the results obtained by the penalty-based method mostly show harsh distribution that leads to not-exactly feasible solutions. As this structure is not braced in global-Y direction, the CI is not the governing-criteria; therefore, as shown in Fig. 11, both of the FIFD and penalty method show satisfied CI. The same situation is inversely established for the 20-story frame; here, CI is the governing-criteria since the structure is braced in both X and Y global directions. Fig. 11

presents the value of DIs for the second example. All DIs are feasible. As shown in Fig.11, CI for all the designs of FIFD methods are feasible and the result of SOS (Fig. 11(d)) is lying on the boundary where the CI equals to the one for an element; while, similar to the 10-story example, two of three designs found by the penalty method have some violated CIs (Fig. 11).

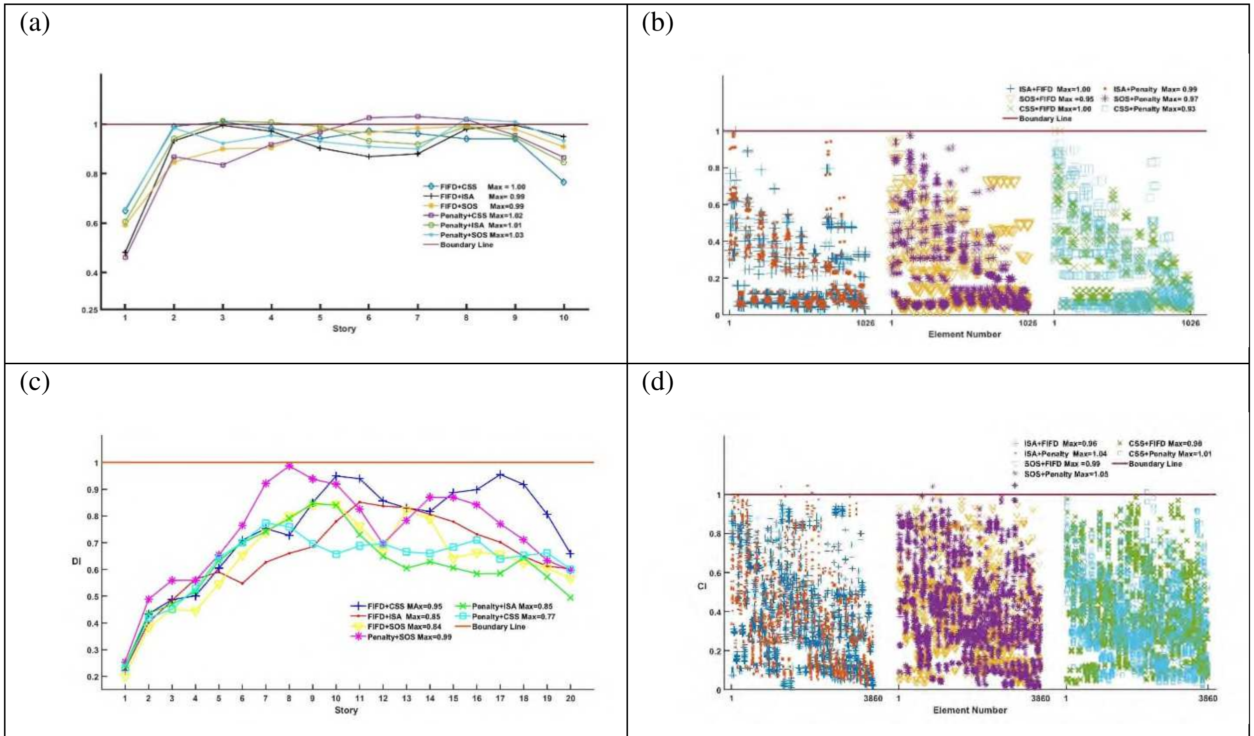

Fig.11 (a) and (b) are the results of DIs and CIs of first example while applying FIFD and Penalty with three optimizers ISA, SOS and CSS. (c) and (d) are the same for the second example.

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Table 9 Sections of the best solution found for tubed-frame for the first time for this example

For the third example, some common penalty techniques (as described in Coello [15]) is utilized. Table 8 shows the best result found by the presented algorithm for this example which is announced for bench-marking purposes. The equivalent weight of this solution is 6779.56 (ton). Maximum DI and Maximum CI of this example are 0.98 and 0.87 Which are feasible and directly found by the algorithm with no handy modifications; the quality of the result shows that it is an on-the-boundary solution, like for the former examples. Fig. 12 show the All-stories DIs and All-elements CIs for this structure, respectively. Fig.13 shows the convergence curvature of mega-braced tubed frame.

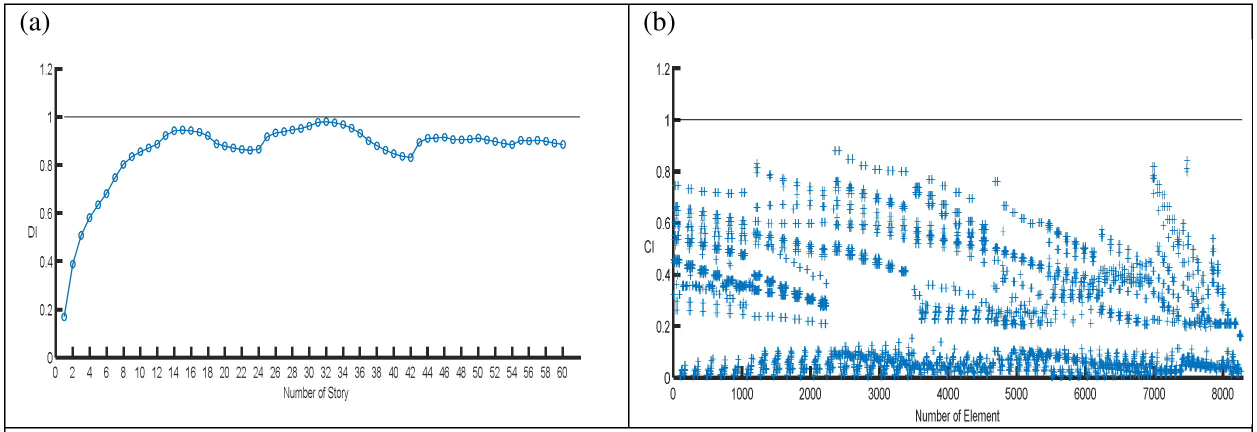

Fig.12 (a) Drift Indices of the final design solution found via the FIFD for the mega-braced 60-story frame; (b) Capacity Indices of the final design solution found via the FIFD for the mega-braced 60-story frame.

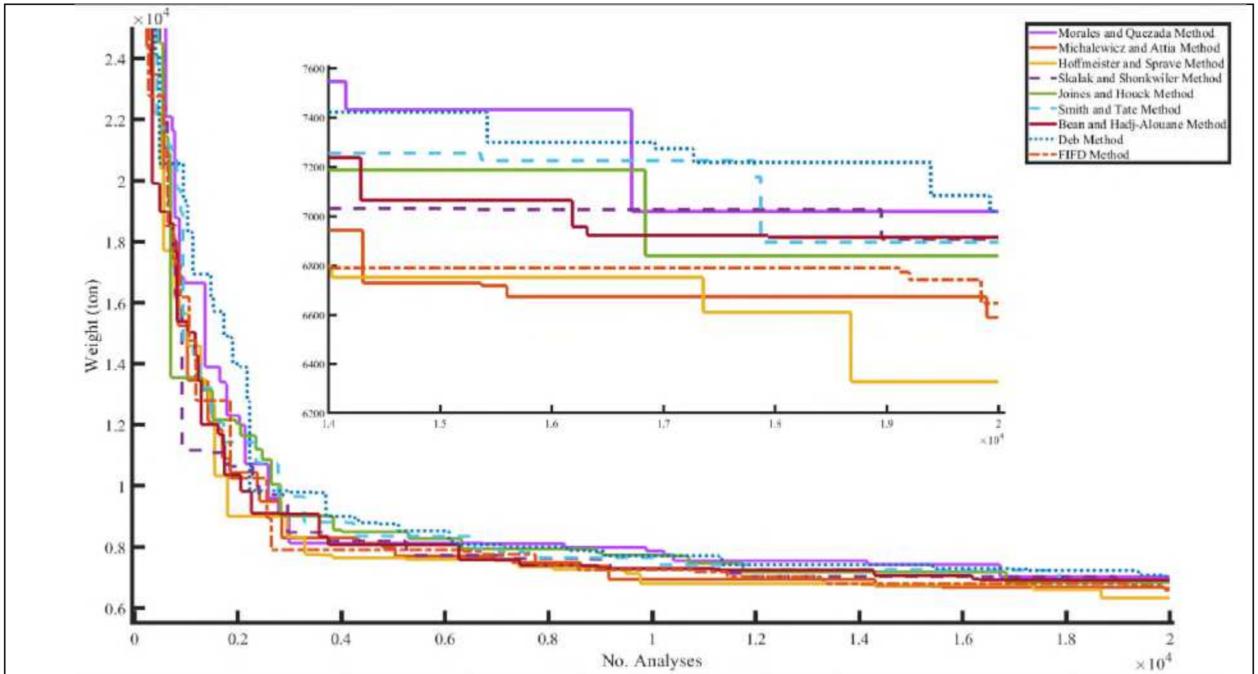

Fig.13 Convergence curvature of the best result of the mega-braced 60-story frame

6.4.2 Statistical results

Table 9 shows statistical comparison among the FIFD and the penalty for the first two examples extracted by the results of 30 independent optimization runs for each algorithm. For the 20-story frame, all the best results for FIFD are lighter than the ones for the penalty while for the 10-story frame, GA (penalty:591.34 against FIFD: 598.28), WOA (Penalty:558.05 against FIFD:560.26) and SOS (penalty: 549.51, against FIFD: 550.61) have provided slightly better results; however, FIFD is still competitive since 5 other algorithms have found better results compared to the penalties. To compare with the results of literature, only GA has found heavier result (i.e. 598.27 (ton) via FIFD) compared to Azad et al. [38] with 584.93 (ton) for the first example and all others are smaller. Similarly, all the best results are lighter than the reported one by Azad & Hasançebi [42] (3539.83 (ton)) for the second example. In the most cases, mean of the finally-converged independent results by FIFD show an absolute superiority against the results of utilized penalty and only WOA has shown a slightly vice versa performance (about only 5 tons just in the first example).

Table 9 Statistical Results for the first and second examples with different optimization methods

Table 10 presents the statistical comparison among the penalty techniques and the FIFD using the CSS algorithm for all examples obtained from 30 number of independent runs. As it is clear from the Table 10, small values of the best and standard deviation are asserted for the FIFD. Not only unstable order of performance was seen in the first two examples, but also poor statistical performance is seen with utilization different penalty techniques. For the first and second examples, standard deviations of results by penalties are too bad and just the penalty by Michalewicz and Attia [56] has shown a better and reasonable performance. Also, just three and two answers among penalties are feasible answers, for the 10 story and X-braced frame, respectively. For the third example, only three out of ten results in Table 10 have weights less than 6780 tons: FIFD, Michalewicz and Attia [56] and Hoffmeister and Sprave [57] with weights equal to 6779.56 (ton), 6720.45 (ton), and 6453.09 (ton); all others have weights more than 6930 tons which clearly sound over-design. The penalty by Deb [58], Skalak and Shonkwiler [59] Bean and Hadj-Alouane [60] has found an over-design structure among all. Although the result obtained by Smith and Tate [61] is on the boundary, interestingly, it has again an over design weight. The best converged results among 30 runs by some of the penalties (i.e. Michalewicz and Attia [56], Hoffmeister and Sprave [57] and Joines and Houck [62]) are infeasible ones and need handy modifications with trial-errors. For the third example, the standard deviations show that absolutely bad distribution of answers has been reported by penalties since the deviation is about 6% to 13% for Joines and Houck [62] as well as Morales and Quezada [63] methods, respectively. However, the deviation for FIFD as well as Michalewicz and Attia [56] are very satisfactory equal to 3% and 2%, respectively, while the answer of FIFD is direct feasible, unlike that obtained by Michalewicz and Attia [56] method.

Table 10 is the statistical results of comparisons for all three problems by different penalties.

7 Concluding Remarks

In this paper, a new technique is developed with a sight to drawbacks of former constraints-handling methods. In addition to the main logic of penalty methods (i.e. the more infeasibility, the more fitness value), three new logics are behind this technique: a) utilizing fuzzy formula to adapt with all structural search spaces, b) idealizing viewpoint to embed designing sight to formula and c) feasibility saving idea. A list of FIFD advantages are as below:

1) There is no necessity for tuning parameters and no trial-errors are in the way which where annoying/impossible tasks.
2) No time-consuming programming is imposed on practical user of this method.

3) Simple versions of meta-heuristics are usable right away and there is no necessity for utilizing Co-Evolutionary algorithms.
4) It is a new constraints-handling specified for structural optimization for the first time.
5) By utilizing FIFD, it does not matter what the topography of the structure is, what type the moment resisting system is and which type of design criteria is governing the design process; Results will remain stable and reliable.
6) The final usual handy manipulation is eliminated which was a very annoying struggle practically; and the final converged results are directly feasible ones.
7) Last and foremost, a valuable expedition in convergence can be observed which provides more facilitation in computations of optimization process.

A prospect list for future works might be as: a) applying this technique on large scale truss and concrete structures since the type of design variables and design criteria are somehow different, b) develop and investigate different forms of formulation for FIFD technique, c) apply this technique on continuous problems instead of skeletal structures.

conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Caption of Tables

Table 1. Parameter summary of the alternative metaheuristic algorithms.

Metaheuristic	***Parameter***	***Description***	***Value***
ACO	N_{ant}	*Colony Size*	*50*
	α	*Intensity of pheromone control parameter*	*1.0*
	β	*Visibility parameter*	*0.4*
	ρ	*Pheromone evaporation*	*0.2*
	ξ	*pheromone trail*	*0.1*
ICA	N_{cont}	*Countries Size*	*50*
	N_{emp}	*Number of Empires/Imperialists*	*10*
	α	*Selection Pressure*	*1*
	β	*Assimilation Coefficient*	*1.5*
	p_r	*Revolution Probability*	*0.05*
	μ	*Revolution Rate*	*0.1*
	ζ	*Colonies Mean Cost Coefficient*	*0.2*
CSS	N_{pop}	*Charged Particle Size*	*50*
	a	*Radius of Charged Sphere*	*0.1*
	$HMCR$	*Harmony Memory Consideration Rate*	*0.85*
	PAR	*Pitch Adjustment Rate*	*0.15*
	kt	*Attract-Repel Coefficient*	*0.9*
	N_{cm}	*Charged Memory Size*	*12*

	k_a	*Acceleration Coefficient*	*0.5*
	k_v	*Velocity Coefficient*	*0.5*
PSO	N_{pop}	*Particle Size*	*50*
	w	*Intertia Coefficient*	*1*
	w_{damp}	*Damping Ratio of Inertia Coefficient*	*0.99*
	C_1	*Personal Acceleration Coefficient*	*2*
	C_2	*Social Acceleration Coefficient*	*2*
FA	N_{pop}	*Fireflies Size*	*50*
	β_0	*Attractiveness parameter*	*1.0*
SOS *WOA* *ISA*	N_{pop}	*Agent Size*	*50*

Table 2 Different utilized penalty methods utilized in the third example; all the formulas are extracted from Coello [15]

Presenters	Formula	Settings Description
Morales and Quezada [63]	$\mathrm{Fitness}(x) = \begin{cases} F(x) & \text{feasible} \\ K - \sum_{1}^{s} \frac{K}{M} & \text{infeasible} \end{cases}$	$K = 1000$ (The author mentions that K is great enough according to dimension of problem, s is the number of satisfied constraints)
Michalewicz and Attia[56]	$\mathrm{Fitness}(x) = F(x) + F(x) \times \frac{1}{2\tau} \sum_{1}^{n} \max(0, g_i(x))^2$	$\tau = 0.99 \times \sqrt{it}$ (arbitrary chosen)
Hoffmeister and Sprave [57]	$\mathrm{Fitness}(x) = F(x) + \sqrt{\sum_{1}^{i} \max\big(0, g_i(x)\big)^2}$	
Skalak and Shonkwiler [59]	$\mathrm{Fitness}(x) = A \times F(x)$	$A = \exp(\frac{-M}{T})$ $T = \frac{1}{\sqrt{it}}$ $M = \sum_{1}^{i} \max\big(0, g_i(x)\big)^2$ (arbitrary chosen)
Joines and Houck [62]	$\mathrm{Fitness}(x) = F(x) + (c \times t)^{\alpha} \times \sum_{1}^{n} \max(0, g_i(x))^{\beta}$	$c = 0.5$ $\alpha = 1$ $\beta = 2$ (These parameters are penalty factors and selected values are inspired from authors of the formula)
Smith and Tate [61]	$\mathrm{Fitness}(x) = F(x) + (B_{feasible} - B_{all})^{\alpha} \times \sum_{1}^{i} \frac{g_i(x)}{b_i}$	$b_i = 0.05$ (b_i is a threshold value for constraints' violation and B is the brevity for 'Best')
Bean and Hadj-Alouane [60]	$\mathrm{Fitness}(x) = F(x) + \lambda(t) \times \sum_{1}^{n} \max\big(0, g_i(x)\big)^2$ $\lambda(t+1) = \begin{cases} \frac{\lambda(t)}{\beta_1} & \text{best is feasible in last K } \mathit{generations} \\ \lambda(t)\beta_2 & \text{best is infeasible in last K } \mathit{generation} \\ \lambda(t) & \text{none of above} \end{cases}$	(arbitrary chosen) $\beta_1 = 1.01$ $\beta_2 = 1.05$
Deb [58]	$\mathrm{Fitness}(x) = \begin{cases} F(x) & \text{feasible} \\ f_{worst} - r \times \sum_{1}^{n} \max\big(0, g_i(x)\big) & \text{infeasible} \end{cases}$	$r = f_{worst}$

(In original form there is no r, but for dimensional objectives in structures, r is included)

[a] G_i

[b] It means iteration in optimization process

Table 3. Design load coefficients according to ASCE [48]

Number	Combination
1	1.4D*
2	1.2D+1.6L*
3	1.2D+0.5L+1(E_x* or W_x*)
4	1.2D+0.5L+1(E_{ex}* or W_{ex}*)
5	1.2D+0.5L+1(E_y or W_y)
6	1.2D+0.5L+1(E_{ey} or W_{ey})
7	0.9D+1(E_x or W_x)
8	0.9D+1(E_{ex} or W_{ex})
9	0.9D+1(E_y or W_y)
10	0.9D+1(E_{ey} or W_{ey})

* D, L, E and W denote Dead, Live, Earthquake and Wind loads, respectively. x and y are loading directions. ex and ey denote loading direction with eccentricity.

Table 4 Optimum results of different algorithms utilizing the FIFD method for the 10-story frame

Stories	Groups	PSO	ACO	FA	GA	ICA	CSS	ISA	SOS	WOA
1	CG1*	'W44X262'	'W14X257'	'W24X192'	'W33X221'	'W14X342'	'W40X277'	'W33X354'	'W36X210'	'W24X192'
	CG2	'W21X101'	'W27X178'	'W30X132'	'W21X132'	'W40X235'	'W36X160'	'W27X161'	'W33X130'	'W36X160'
	CG3	'W30X191'	'W18X283'	'W24X104'	'W24X192'	'W14X120'	'W24X117'	'W24X250'	'W30X108'	'W14X99'
	CG4	'W40X249'	'W27X146'	'W12X170'	'W40X392'	'W36X170'	'W27X178'	'W40X211'	'W24X176'	'W27X161'
	CG5	'W30X148'	'W40X321'	'W30X292'	'W30X391'	'W40X297'	'W36X170'	'W14X211'	'W12X305'	'W12X336'
	IB*	'W16X26'	'W8X28'	'W14X74'	'W27X84'	'W8X18'	'W8X28'	'W24X68'	'W24X68'	'W21X73'
	OB*	'W30X90'	'W24X68'	'W27X94'	'W8X40'	'W24X76'	'W30X90'	'W14X48'	'W24X76'	'W16X89'
	BR*	'W18X76'	'W8X24'	'W16X67'	'W8X31'	'W24X62'	'W8X28'	'W21X50'	'W10X68'	'W16X67'

2-4	CG1	'W21X166'	'W30X235'	'W40X297'	'W36X230'	'W30X211'	'W40X372'	'W36X300'	'W40X277'	'W36X300'
	CG2	'W30X116'	'W14X132'	'W12X230'	'W24X192'	'W40X149'	'W40X167'	'W14X176'	'W30X261'	'W14X233'
	CG3	'W27X94'	'W27X217'	'W40X149'	'W21X93'	'W27X102'	'W40X174'	'W40X167'	'W33X118'	'W30X132'
	CG4	'W24X176'	'W27X114'	'W21X122'	'W18X106'	'W33X118'	'W36X160'	'W18X158'	'W24X117'	'W27X114'
	CG5	'W14X99'	'W30X173'	'W36X256'	'W12X210'	'W21X132'	'W21X166'	'W27X114'	'W33X241'	'W18X258'
	IB	'W27X84'	'W18X40'	'W14X26'	'W27X94'	'W24X84'	'W24X55'	'W21X50'	'W16X31'	'W14X22'
	OB	'W16X40'	'W33X130'	'W40X149'	'W18X35'	'W18X46'	'W21X44'	'W24X76'	'W33X118'	'W36X135'
	BR	'W24X76'	'W12X72'	'W8X58'	'W14X74'	'W12X53'	'W14X53'	'W14X68'	'W8X48'	'W21X62'
5-7	CG1	'W36X245'	'W24X162'	'W36X245'	'W40X249'	'W27X217'	'W14X145'	'W40X235'	'W18X258'	'W30X235'
	CG2	'W12X136'	'W12X170'	'W18X106'	'W27X146'	'W14X109'	'W24X117'	'W14X176'	'W12X120'	'W12X96'
	CG3	'W36X170'	'W27X94'	'W30X116'	'W24X76'	'W12X106'	'W27X161'	'W30X99'	'W30X148'	'W33X118'
	CG4	'W36X135'	'W40X199'	'W27X94'	'W30X261'	'W44X230'	'W24X103'	'W18X119'	'W18X86'	'W18X86'
	CG5	'W10X112'	'W30X191'	'W12X190'	'W24X76'	'W24X94'	'W14X159'	'W36X150'	'W33X169'	'W40X174'
	IB	'W18X40'	'W18X55'	'W21X44'	'W21X57'	'W18X65'	'W27X84'	'W21X62'	'W24X55'	'W21X44'
	OB	'W40X149'	'W30X99'	'W24X68'	'W30X99'	'W24X62'	'W21X57'	'W27X102'	'W21X68'	'W24X84'
	BR	'W10X68'	'W12X50'	'W12X87'	'W10X39'	'W8X48'	'W8X58'	'W14X68'	'W14X68'	'W16X77'
8-10	CG1	'W30X132'	'W27X258'	'W18X76'	'W16X77'	'W21X73'	'W33X130'	'W10X68'	'W12X87'	'W24X76'
	CG2	'W27X178'	'W12X152'	'W21X57'	'W14X99'	'W12X79'	'W14X193'	'W24X104'	'W12X40'	'W18X50'
	CG3	'W14X53'	'W27X146'	'W30X124'	'W18X192'	'W12X50'	'W16X57'	'W21X44'	'W27X114'	'W30X124'
	CG4	'W14X90'	'W30X108'	'W33X201'	'W12X45'	'W44X230'	'W18X76'	'W24X68'	'W33X201'	'W40X199'
	CG5	'W12X152'	'W14X193'	'W21X101'	'W24X207'	'W33X201'	'W18X143'	'W14X99'	'W21X122'	'W27X114'
	IB	'W18X55'	'W18X35'	'W18X55'	'W10X26'	'W24X62'	'W16X26'	'W18X46'	'W21X44'	'W21X50'
	OB	'W18X40'	'W14X30'	'W16X26'	'W27X84'	'W8X18'	'W21X83'	'W10X22'	'W8X18'	'W10X22'
	BR	'W14X38'	'W12X50'	'W27X84'	'W16X45'	'W16X57'	'W16X40'	'W21X62'	'W14X61'	'W21X83'
Weight (ton)		581.05	578.96	576.45	598.97	568.48	543.02	559.32	550.61	560.26
Max Drift Index		0.95	0.99	0.99	0.98	0.99	1.00	0.99	0.99	0.98
Max Capacity Index		0.89	0.90	0.99	0.98	0.92	0.96	0.94	0.95	0.91
Practical Weight		581.05	578.96	576.45	598.97	568.48	543.02	559.32	550.61	560.26

Table 5 Optimum results of different algorithms utilizing the penalty method for the 10-story frame

Stories	Groups	Azad et al. [31]	PSO	ACO	FA	GA	ICA	CSS	ISA	SOS	WOA
1	CG1*	'W33X201'	'W18X192'	'W18X143'	'W21X147'	'W30X211'	'W14X455'	'W40X211'	'W18X283'	'W36X359'	'W33X318'
	CG2	'W24X146'	'W27X146'	'W24X131'	'W27X161'	'W24X146'	'W21X122'	'W30X124'	'W40X199'	'W40X278'	'W24X192'
	CG3	'W24X104'	'W16X100'	'W40X199'	'W18X175'	'W10X112'	'W21X147'	'W30X211'	'W30X108'	'W40X431'	'W30X116'
	CG4	'W40X174'	'W14X159'	'W30X191'	'W30X191'	'W14X176'	'W24X162'	'W36X150'	'W24X176'	'W24X117'	'W40X174'

	CG5	'W40X321'	'W14X342'	'W36X160'	'W18X158'	'W14X311'	'W33X130'	'W14X159'	'W36X135'	'W30X211'	'W21X201'
	IB*	'W27X84'	'W24X84'	'W33X118'	'W24X94'	'W18X86'	'W24X55'	'W10X30'	'W21X50'	'W8X21'	'W8X24'
	OB*	'W27X84'	'W14X90'	'W12X58'	'W14X43'	'W24X76'	'W18X60'	'W27X84'	'W24X84'	'W21X73'	'W33X118'
	BR*	'W18X76'	'W14X74'	'W33X152'	'W12X65'	'W10X68'	'W14X90'	'W12X65'	'W21X50'	'W18X76'	'W8X24'
2-4	CG1	'W36X328'	'W33X318'	'W12X152'	'W27X129'	'W27X307'	'W40X167'	'W44X230'	'W40X215'	'W40X249'	'W40X278'
	CG2	'W36X245'	'W36X232'	'W14X176'	'W21X166'	'W36X260'	'W30X211'	'W33X118'	'W40X199'	'W33X169'	'W24X207'
	CG3	'W36X135'	'W33X141'	'W30X148'	'W21X201'	'W27X146'	'W36X150'	'W40X149'	'W27X178'	'W30X99'	'W40X183'
	CG4	'W33X118'	'W27X129'	'W21X111'	'W12X106'	'W33X118'	'W30X124'	'W27X146'	'W33X169'	'W30X99'	'W24X146'
	CG5	'W44X262'	'W40X278'	'W21X111'	'W30X124'	'W40X278'	'W30X99'	'W12X120'	'W24X176'	'W21X182'	'W27X146'
	IB	'W16X26'	'W16X31'	'W24X55'	'W24X68'	'W10X26'	'W16X40'	'W24X94'	'W24X55'	'W27X84'	'W14X26'
	OB	'W36X135'	'W40X149'	'W24X84'	'W33X118'	'W33X130'	'W33X130'	'W12X26'	'W14X61'	'W14X26'	'W27X129'
	BR	'W21X62'	'W8X67'	'W24X76'	'W24X76'	'W18X65'	'W10X54'	'W10X49'	'W14X74'	'W10X60'	'W10X68'
5-7	CG1	'W27X258'	'W33X241'	'W40X183'	'W30X148'	'W18X258'	'W40X174'	'W18X158'	'W36X182'	'W30X148'	'W30X124'
	CG2	'W18X106'	'W14X109'	'W14X109'	'W14X120'	'W21X111'	'W27X178'	'W40X199'	'W18X234'	'W21X122'	'W30X191'
	CG3	'W33X130'	'W33X118'	'W30X132'	'W27X114'	'W33X118'	'W27X161'	'W36X135'	'W30X108'	'W18X119'	'W27X129'
	CG4	'W27X94'	'W18X97'	'W21X83'	'W21X111'	'W27X102'	'W33X169'	'W24X131'	'W14X132'	'W27X161'	'W16X89'
	CG5	'W24X192'	'W24X176'	'W24X207'	'W24X131'	'W14X176'	'W33X141'	'W36X182'	'W27X146'	'W27X102'	'W27X84'
	IB	'W21X44'	'W18X46'	'W18X50'	'W12X65'	'W16X45'	'W24X62'	'W24X55'	'W24X68'	'W21X57'	'W21X68'
	OB	'W21X73'	'W24X76'	'W30X90'	'W30X116'	'W24X84'	'W24X103'	'W36X135'	'W24X76'	'W18X46'	'W30X99'
	BR	'W30X90'	'W14X90'	'W12X79'	'W18X71'	'W16X89'	'W16X31'	'W14X61'	'W10X49'	'W21X62'	'W30X90'
8-10	CG1	'W18X86'	'W24X76'	'W24X62'	'W36X160'	'W16X77'	'W24X84'	'W18X40'	'W16X77'	'W14X53'	'W24X84'
	CG2	'W21X50'	'W10X54'	'W30X173'	'W14X99'	'W18X55'	'W30X99'	'W18X106'	'W14X90'	'W14X120'	'W14X145'
	CG3	'W36X135'	'W27X129'	'W21X122'	'W30X116'	'W24X131'	'W18X46'	'W18X86'	'W30X132'	'W12X120'	'W8X40'
	CG4	'W33X201'	'W14X211'	'W14X74'	'W21X111'	'W40X215'	'W12X87'	'W24X68'	'W18X130'	'W33X141'	'W24X76'
	CG5	'W30X108'	'W14X99'	'W12X120'	'W21X73'	'W24X117'	'W14X68'	'W12X120'	'W8X35'	'W16X77'	'W14X109'
	IB	'W21X57'	'W24X55'	'W21X50'	'W14X43'	'W24X55'	'W14X43'	'W14X34'	'W14X34'	'W16X36'	'W16X45'
	OB	'W16X26'	'W8X21'	'W24X76'	'W21X44'	'W14X26'	'W24X55'	'W21X50'	'W21X50'	'W21X73'	'W10X22'
	BR	'W18X76'	'W24X68'	'W12X58'	'W30X90'	'W18X76'	'W14X48'	'W12X45'	'W14X38'	'W18X55'	'W18X71'
Weight (ton)		584.93	591.36	591.53	595.71	591.34	571.03	549.24	563.19	549.51	558.05
Max Drift Index		_	1.00	0.97	1.00	1.04	1.00	1.02	1.01	1.03	1.03
Max Capacity Index		_	0.89	0.90	0.88	0.92	0.99	0.93	0.99	0.97	1.03
Practical Weight		584.93	591.36	591.53	595.71	612.08	571.03	561.13	585.74	558.23	569.55

Table 6 Optimum results of different algorithms utilizing the FIFD method for the 20-story frame

Story	Group	PSO	ACO	FA	GA	ICA	CSS	ISA	SOS	WOA
1-2	*CG1	'W36X256'	'W33X221'	'W12X210'	'W12X45'	'W18X106'	'W40X466'	'W14X211'	'W14X283'	'W33X291'
	CG2	'W33X291'	'W36X280'	'W21X147'	'W14X233'	'W30X235'	'W18X234'	'W14X145'	'W18X311'	'W30X235'
	CG3	'W30X477'	'W30X235'	'W40X264'	'W36X300'	'W36X230'	'W12X190'	'W33X201'	'W40X264'	'W33X221'
	CG4	'W18X234'	'W36X194'	'W24X492'	'W40X297'	'W33X263'	'W30X391'	'W24X207'	'W12X305'	'W14X500'
	CG5	'W14X257'	'W40X215'	'W12X106'	'W24X207'	'W14X120'	'W21X101'	'W21X147'	'W36X170'	'W24X117'
	*IB	'W18X55'	'W30X116'	'W21X68'	'W18X86'	'W30X108'	'W16X67'	'W27X84'	'W18X55'	'W21X73'
	*OB	'W8X58'	'W24X62'	'W16X67'	'W12X96'	'W8X58'	'W14X120'	'W12X50'	'W21X68'	'W12X106'
	*BR	'W24X94'	'W12X53'	'W8X40'	'W14X68'	'W8X40'	'W8X48'	'W8X58'	'W10X68'	'W14X61'
3-4	CG1	'W12X336'	'W40X277'	'W40X235'	'W27X194'	'W24X176'	'W27X102'	'W33X118'	'W27X307'	'W14X90'
	CG2	'W40X167'	'W14X398'	'W18X143'	'W33X152'	'W36X182'	'W36X300'	'W18X130'	'W12X305'	'W30X326'
	CG3	'W12X305'	'W36X300'	'W40X215'	'W40X297'	'W12X336'	'W14X211'	'W36X232'	'W21X147'	'W24X250'
	CG4	'W12X210'	'W36X280'	'W40X321'	'W36X182'	'W44X262'	'W40X503'	'W27X217'	'W40X392'	'W14X342'
	CG5	'W14X176'	'W14X193'	'W30X148'	'W36X230'	'W36X160'	'W14X90'	'W21X132'	'W40X264'	'W24X207'
	IB	'W24X62'	'W18X60'	'W21X101'	'W14X99'	'W18X55'	'W24X131'	'W21X62'	'W30X116'	'W24X68'
	OB	'W18X71'	'W21X101'	'W21X101'	'W18X119'	'W16X67'	'W12X58'	'W16X89'	'W21X68'	'W27X102'
	BR	'W10X54'	'W18X76'	'W24X68'	'W18X76'	'W21X111'	'W14X61'	'W14X68'	'W8X40'	'W8X40'
5-6	CG1	'W10X26'	'W16X40'	'W33X201'	'W12X120'	'W36X182'	'W16X31'	'W12X58'	'W18X143'	'W30X90'
	CG2	'W12X210'	'W30X132'	'W21X93'	'W24X94'	'W24X117'	'W36X210'	'W14X211'	'W30X132'	'W18X119'
	CG3	'W36X210'	'W33X354'	'W12X230'	'W27X235'	'W40X331'	'W18X119'	'W33X263'	'W33X221'	'W33X241'
	CG4	'W12X152'	'W12X136'	'W40X235'	'W14X605'	'W27X307'	'W36X328'	'W24X408'	'W14X283'	'W14X311'
	CG5	'W30X235'	'W27X161'	'W24X94'	'W36X439'	'W30X124'	'W12X120'	'W30X148'	'W40X593'	'W16X100'
	IB	'W16X57'	'W30X90'	'W12X58'	'W16X77'	'W21X73'	'W24X68'	'W27X114'	'W24X76'	'W21X83'
	OB	'W18X130'	'W30X148'	'W14X68'	'W36X182'	'W24X94'	'W18X86'	'W14X53'	'W12X65'	'W21X68'
	BR	'W14X61'	'W10X49'	'W21X73'	'W30X116'	'W14X82'	'W14X61'	'W10X39'	'W14X48'	'W12X50'
7-8	CG2	'W12X120'	'W18X211'	'W18X76'	'W14X99'	'W30X173'	'W44X335'	'W24X131'	'W27X129'	'W21X166'
	CG3	'W40X297'	'W27X194'	'W40X372'	'W36X150'	'W27X368'	'W14X257'	'W21X201'	'W24X492'	'W24X192'
	CG4	'W14X90'	'W30X261'	'W30X235'	'W27X217'	'W14X257'	'W30X391'	'W21X132'	'W24X229'	'W24X279'
	CG5	'W30X477'	'W40X249'	'W14X68'	'W44X230'	'W18X192'	'W12X72'	'W12X106'	'W14X145'	'W12X152'
	IB	'W30X108'	'W27X102'	'W18X60'	'W21X62'	'W27X114'	'W24X94'	'W24X62'	'W16X57'	'W24X62'
	OB	'W14X48'	'W21X73'	'W30X173'	'W12X152'	'W12X58'	'W30X99'	'W30X326'	'W21X73'	'W21X182'
	BR	'W12X58'	'W14X99'	'W10X49'	'W12X72'	'W8X58'	'W8X31'	'W14X61'	'W10X54'	'W8X48'
9-10	CG2	'W36X280'	'W36X280'	'W30X132'	'W14X61'	'W33X130'	'W21X101'	'W24X104'	'W18X106'	'W24X131'

	CG3	'W33X318'	'W36X280'	'W12X190'	'W27X448'	'W40X264'	'W16X100'	'W44X290'	'W30X116'	'W24X250'
	CG4	'W12X87'	'W27X307'	'W14X665'	'W10X112'	'W21X132'	'W24X162'	'W18X119'	'W33X152'	'W14X283'
	CG5	'W12X252'	'W24X117'	'W18X234'	'W12X120'	'W27X94'	'W24X84'	'W21X111'	'W40X149'	'W16X67'
	IB	'W12X79'	'W30X116'	'W36X160'	'W27X84'	'W30X124'	'W10X49'	'W16X57'	'W12X72'	'W18X86'
	OB	'W14X109'	'W18X106'	'W12X65'	'W24X62'	'W8X48'	'W14X48'	'W21X68'	'W21X101'	'W36X194'
	BR	'W12X65'	'W12X106'	'W21X62'	'W10X68'	'W8X48'	'W14X90'	'W18X97'	'W12X53'	'W24X104'
11-12	CG2	'W24X229'	'W18X106'	'W21X68'	'W18X86'	'W14X82'	'W14X99'	'W14X99'	'W16X67'	'W40X199'
	CG3	'W18X283'	'W10X112'	'W44X230'	'W36X245'	'W18X119'	'W18X192'	'W14X257'	'W40X331'	'W12X79'
	CG4	'W21X111'	'W36X210'	'W36X359'	'W27X539'	'W18X258'	'W24X492'	'W24X117'	'W40X199'	'W27X161'
	CG5	'W40X321'	'W24X335'	'W8X58'	'W12X279'	'W40X149'	'W14X99'	'W30X173'	'W14X90'	'W12X96'
	IB	'W18X60'	'W24X103'	'W30X132'	'W24X146'	'W21X68'	'W21X62'	'W18X86'	'W27X129'	'W30X108'
	OB	'W14X90'	'W14X145'	'W21X147'	'W14X109'	'W12X53'	'W36X135'	'W18X55'	'W16X100'	'W8X48'
	BR	'W18X76'	'W6X16'	'W16X67'	'W24X94'	'W16X77'	'W14X48'	'W14X61'	'W8X35'	'W8X40'
13-14	CG2	'W18X311'	'W24X104'	'W21X101'	'W30X235'	'W24X279'	'W40X183'	'W33X152'	'W14X99'	'W21X93'
	CG3	'W33X169'	'W12X136'	'W40X174'	'W12X120'	'W24X162'	'W27X102'	'W12X305'	'W10X100'	'W18X311'
	CG4	'W12X79'	'W36X256'	'W30X116'	'W10X88'	'W36X194'	'W30X326'	'W10X60'	'W14X99'	'W33X201'
	CG5	'W30X261'	'W18X258'	'W18X97'	'W36X160'	'W18X60'	'W10X68'	'W33X291'	'W14X99'	'W21X132'
	IB	'W21X68'	'W16X57'	'W24X68'	'W24X68'	'W8X48'	'W24X104'	'W18X106'	'W24X94'	'W12X79'
	OB	'W40X167'	'W21X147'	'W8X48'	'W10X112'	'W18X65'	'W10X88'	'W18X86'	'W27X84'	'W24X94'
	BR	'W24X104'	'W14X43'	'W8X48'	'W14X61'	'W14X43'	'W8X31'	'W10X60'	'W8X40'	'W10X60'
15-16	CG2	'W30X191'	'W10X88'	'W24X162'	'W12X58'	'W14X48'	'W30X148'	'W44X335'	'W21X101'	'W10X60'
	CG3	'W33X130'	'W40X167'	'W44X262'	'W14X370'	'W21X62'	'W12X120'	'W24X162'	'W24X192'	'W27X178'
	CG4	'W44X335'	'W10X88'	'W27X217'	'W21X93'	'W14X257'	'W24X103'	'W10X77'	'W44X262'	'W40X167'
	CG5	'W21X147'	'W33X318'	'W21X62'	'W18X60'	'W40X167'	'W14X68'	'W16X67'	'W18X97'	'W40X297'
	IB	'W18X76'	'W10X77'	'W16X57'	'W10X60'	'W27X129'	'W16X67'	'W14X48'	'W14X82'	'W24X103'
	OB	'W36X160'	'W24X62'	'W30X108'	'W12X190'	'W27X146'	'W14X48'	'W30X148'	'W18X97'	'W30X90'
	BR	'W8X31'	'W8X31'	'W18X50'	'W27X161'	'W12X53'	'W18X71'	'W8X31'	'W8X48'	'W10X33'
17-18	CG2	'W21X101'	'W27X114'	'W27X307'	'W8X48'	'W33X141'	'W14X48'	'W12X65'	'W21X50'	'W18X192'
	CG3	'W16X57'	'W14X53'	'W33X241'	'W40X211'	'W36X150'	'W27X84'	'W21X201'	'W18X130'	'W8X67'
	CG4	'W30X292'	'W16X57'	'W36X260'	'W36X300'	'W14X90'	'W18X60'	'W16X67'	'W36X182'	'W33X130'
	CG5	'W12X79'	'W24X229'	'W30X235'	'W36X393'	'W14X61'	'W30X99'	'W18X86'	'W18X71'	'W36X135'
	IB	'W18X55'	'W12X170'	'W30X116'	'W36X182'	'W18X60'	'W10X54'	'W30X116'	'W40X149'	'W24X104'
	OB	'W24X103'	'W12X53'	'W10X88'	'W18X71'	'W14X109'	'W12X79'	'W10X60'	'W8X48'	'W8X67'
	BR	'W10X60'	'W8X67'	'W8X28'	'W16X40'	'W10X77'	'W8X31'	'W8X31'	'W8X31'	'W24X68'

19-20	CG2	'W30X235'	'W14X120'	'W8X67'	'W30X116'	'W21X132'	'W14X30'	'W14X43'	'W14X90'	'W24X146'
	CG3	'W12X96'	'W12X30'	'W21X147'	'W21X132'	'W8X31'	'W16X50'	'W14X68'	'W14X30'	'W21X73'
	CG4	'W24X146'	'W14X38'	'W44X290'	'W18X211'	'W44X230'	'W14X48'	'W10X30'	'W36X160'	'W10X45'
	CG5	'W24X146'	'W12X136'	'W14X48'	'W24X335'	'W12X106'	'W12X96'	'W40X235'	'W21X68'	'W12X65'
	IB	'W12X136'	'W18X106'	'W24X76'	'W16X77'	'W12X120'	'W24X103'	'W12X58'	'W21X68'	'W16X57'
	OB	'W12X87'	'W18X192'	'W21X83'	'W40X199'	'W30X99'	'W18X65'	'W14X99'	'W12X53'	'W14X109'
	BR	'W6X15'	'W8X24'	'W6X20'	'W14X193'	'W6X20'	'W10X33'	'W24X104'	'W8X28'	'W12X79'
Weight (ton)		2993.51	3112.13	3036.29	3614.55	2913.79	2713.57	2817.29	2775.39	2921.28
Max Drift Index		0.85	0.8	0.69	0.74	0.91	0.97	0.85	0.92	0.92
Max Capacity Index		1.00	0.98	0.99	1.00	0.99	0.98	0.96	0.99	0.99
Practical weight		2993.51	3112.13	3036.29	3614.55	2913.79	2713.57	2817.29	2775.39	2921.28

Table 7 Optimum results of different algorithms utilizing the penalty method for the 20-story frame

Story	Group	Ref. [35]	PSO	ACO	FA	GA	ICA	CSS	ISA	SOS	WOA
1-2	*CG1	'W24X94'	'W27X178'	'W24X207'	'W18X55'	'W14X109'	'W33X241'	'W21X83'	'W10X88'	'W18X192'	'W12X305'
	CG2	'W27X368'	'W21X166'	'W12X190'	'W12X136'	'W12X79'	'W36X256'	'W18X175'	'W27X235'	'W24X146'	'W21X182'
	CG3	'W30X477'	'W30X326'	'W12X230'	'W36X300'	'W33X221'	'W14X455'	'W36X182'	'W33X201'	'W12X230'	'W14X257'
	CG4	'W40X199'	'W44X335'	'W36X328'	'W40X199'	'W36X527'	'W18X106'	'W14X455'	'W24X492'	'W24X492'	'W24X192'
	CG5	'W30X191'	'W33X241'	'W36X160'	'W18X143'	'W36X160'	'W12X190'	'W40X167'	'W21X166'	'W36X170'	'W33X221'
	*IB	'W12X152'	'W24X76'	'W18X50'	'W24X68'	'W30X148'	'W27X84'	'W18X71'	'W24X62'	'W12X50'	'W27X84'
	*OB	'W10X30'	'W12X65'	'W18X50'	'W18X76'	'W24X117'	'W18X50'	'W12X53'	'W30X99'	'W16X57'	'W18X65'
	*BR	'W14X82'	'W14X26'	'W12X58'	'W12X53'	'W21X73'	'W24X84'	'W12X72'	'W12X40'	'W14X68'	'W12X53'
3-4	CG1	'W18X65'	'W18X211'	'W27X368'	'W10X49'	'W36X230'	'W12X190'	'W10X54'	'W21X111'	'W24X94'	'W14X43'
	CG2	'W36X439'	'W21X122'	'W40X215'	'W36X160'	'W10X77'	'W40X249'	'W27X161'	'W40X174'	'W18X130'	'W30X235'
	CG3	'W44X335'	'W40X264'	'W24X279'	'W40X297'	'W27X368'	'W18X258'	'W27X146'	'W24X162'	'W12X252'	'W33X291'
	CG4	'W36X170'	'W27X161'	'W27X448'	'W21X201'	'W33X354'	'W21X111'	'W24X335'	'W18X283'	'W33X291'	'W40X174'
	CG5	'W30X191'	'W36X260'	'W14X283'	'W33X241'	'W18X106'	'W12X336'	'W30X191'	'W12X136'	'W33X141'	'W27X258'
	IB	'W14X176'	'W14X53'	'W24X76'	'W24X103'	'W14X74'	'W14X48'	'W24X68'	'W27X84'	'W30X90'	'W21X83'
	OB	'W12X40'	'W18X71'	'W24X104'	'W10X45'	'W33X291'	'W27X84'	'W14X68'	'W24X104'	'W24X94'	'W24X117'
	BR	'W18X119'	'W27X146'	'W10X17'	'W24X68'	'W14X74'	'W10X112'	'W18X158'	'W8X67'	'W12X50'	'W30X108'
5-6	CG1	'W18X71'	'W21X111'	'W18X97'	'W24X94'	'W12X87'	'W30X148'	'W30X173'	'W12X50'	'W14X176'	'W27X178'
	CG2	'W44X335'	'W36X232'	'W24X192'	'W27X114'	'W18X234'	'W33X152'	'W18X158'	'W14X311'	'W40X199'	'W24X103'
	CG3	'W40X297'	'W33X141'	'W27X161'	'W27X161'	'W30X191'	'W14X500'	'W36X135'	'W14X455'	'W27X307'	'W30X326'
	CG4	'W36X160'	'W18X234'	'W36X328'	'W33X169'	'W36X300'	'W14X90'	'W30X292'	'W18X258'	'W27X235'	'W33X169'
	CG5	'W27X161'	'W36X150'	'W40X466'	'W18X119'	'W14X120'	'W18X158'	'W21X147'	'W12X210'	'W24X104'	'W36X256'

	IB	'W18X71'	'W18X71'	'W21X93'	'W14X61'	'W33X130'	'W21X73'	'W14X90'	'W24X68'	'W18X55'	'W24X103'
	OB	'W27X114'	'W12X53'	'W30X235'	'W18X86'	'W44X335'	'W27X129'	'W30X116'	'W30X132'	'W18X60'	'W8X48'
	BR	'W33X152'	'W10X88'	'W12X79'	'W16X89'	'W14X43'	'W10X19'	'W14X61'	'W14X53'	'W16X67'	'W14X74'
7-8	CG2	'W40X235'	'W18X234'	'W18X106'	'W24X104'	'W12X58'	'W12X96'	'W40X167'	'W24X207'	'W14X99'	'W10X100'
	CG3	'W24X207'	'W40X215'	'W36X280'	'W40X167'	'W14X550'	'W40X215'	'W40X392'	'W27X217'	'W12X190'	'W18X258'
	CG4	'W14X159'	'W27X368'	'W30X173'	'W33X152'	'W30X326'	'W14X61'	'W44X335'	'W40X593'	'W14X176'	'W14X193'
	CG5	'W12X210'	'W21X182'	'W12X136'	'W18X143'	'W27X235'	'W40X392'	'W27X539'	'W8X67'	'W21X101'	'W14X176'
	IB	'W30X99'	'W21X93'	'W14X90'	'W12X72'	'W14X82'	'W12X50'	'W24X76'	'W14X90'	'W12X58'	'W21X83'
	OB	'W8X35'	'W24X76'	'W36X135'	'W24X117'	'W21X73'	'W12X136'	'W12X53'	'W14X109'	'W10X88'	'W18X86'
	BR	'W12X53'	'W24X68'	'W8X35'	'W10X60'	'W12X22'	'W30X124'	'W8X35'	'W18X60'	'W8X67'	'W6X16'
9-10	CG2	'W36X194'	'W18X76'	'W14X145'	'W40X277'	'W14X82'	'W18X119'	'W18X106'	'W18X258'	'W27X84'	'W40X235'
	CG3	'W24X250'	'W36X150'	'W40X235'	'W40X211'	'W14X398'	'W18X175'	'W30X326'	'W14X283'	'W12X305'	'W36X245'
	CG4	'W40X183'	'W40X235'	'W40X331'	'W24X146'	'W14X233'	'W8X58'	'W44X262'	'W27X368'	'W30X391'	'W30X116'
	CG5	'W21X147'	'W40X211'	'W14X99'	'W21X93'	'W12X230'	'W12X230'	'W12X87'	'W12X58'	'W30X108'	'W33X263'
	IB	'W40X211'	'W30X99'	'W40X149'	'W16X57'	'W14X53'	'W14X53'	'W30X90'	'W16X57'	'W14X82'	'W12X96'
	OB	'W30X124'	'W18X192'	'W12X50'	'W18X175'	'W18X211'	'W18X65'	'W14X74'	'W21X73'	'W10X49'	'W24X68'
	BR	'W18X76'	'W8X31'	'W24X84'	'W14X82'	'W10X33'	'W14X74'	'W30X124'	'W12X45'	'W12X87'	'W12X45'
11-12	CG2	'W21X182'	'W40X211'	'W27X194'	'W14X193'	'W44X230'	'W24X84'	'W14X74'	'W10X60'	'W30X211'	'W8X67'
	CG3	'W12X210'	'W40X277'	'W24X192'	'W14X370'	'W21X122'	'W12X170'	'W33X141'	'W36X210'	'W36X245'	'W27X307'
	CG4	'W24X192'	'W33X141'	'W24X408'	'W24X229'	'W36X232'	'W14X61'	'W40X199'	'W40X278'	'W33X201'	'W14X145'
	CG5	'W24X162'	'W40X278'	'W10X100'	'W24X207'	'W30X108'	'W14X90'	'W36X300'	'W24X84'	'W24X117'	'W40X215'
	IB	'W40X149'	'W18X71'	'W18X60'	'W30X90'	'W27X94'	'W24X62'	'W30X90'	'W30X124'	'W21X68'	'W33X118'
	OB	'W10X54'	'W27X161'	'W10X45'	'W10X54'	'W21X101'	'W18X86'	'W18X71'	'W21X132'	'W36X232'	'W14X68'
	BR	'W16X67'	'W14X43'	'W8X15'	'W16X67'	'W33X141'	'W21X101'	'W12X22'	'W8X31'	'W6X12'	'W10X60'
13-14	CG2	'W14X159'	'W18X97'	'W24X229'	'W18X258'	'W12X58'	'W14X90'	'W30X90'	'W30X116'	'W21X101'	'W21X83'
	CG3	'W40X264'	'W40X277'	'W14X311'	'W40X297'	'W24X162'	'W40X277'	'W18X143'	'W40X167'	'W36X328'	'W33X263'
	CG4	'W27X102'	'W21X201'	'W44X230'	'W27X161'	'W18X76'	'W8X40'	'W24X192'	'W40X211'	'W18X143'	'W40X149'
	CG5	'W27X129'	'W36X182'	'W18X60'	'W24X62'	'W33X263'	'W12X252'	'W33X118'	'W18X175'	'W18X143'	'W12X72'
	IB	'W10X77'	'W16X77'	'W24X117'	'W40X149'	'W12X50'	'W33X241'	'W36X135'	'W27X84'	'W16X57'	'W30X90'
	OB	'W33X318'	'W12X72'	'W33X152'	'W10X77'	'W24X408'	'W14X68'	'W30X124'	'W8X58'	'W14X74'	'W12X79'
	BR	'W16X67'	'W12X72'	'W16X77'	'W8X58'	'W33X221'	'W14X120'	'W8X40'	'W8X48'	'W8X58'	'W16X100'
15-16	CG2	'W18X86'	'W12X79'	'W36X232'	'W12X106'	'W12X58'	'W30X132'	'W14X53'	'W14X61'	'W36X194'	'W12X79'
	CG3	'W36X232'	'W10X77'	'W24X131'	'W36X232'	'W27X178'	'W21X166'	'W10X68'	'W44X290'	'W18X71'	'W40X149'

	CG4	'W14X90'	'W24X94'	'W24X229'	'W40X277'	'W40X211'	'W24X250'	'W30X292'	'W40X321'	'W40X199'	'W30X292'
	CG5	'W12X79'	'W27X539'	'W14X132'	'W14X132'	'W12X45'	'W12X305'	'W10X68'	'W8X58'	'W14X311'	'W36X245'
	IB	'W27X129'	'W14X53'	'W12X87'	'W36X135'	'W21X132'	'W24X62'	'W24X68'	'W30X132'	'W10X60'	'W12X79'
	OB	'W10X26'	'W12X170'	'W33X130'	'W8X48'	'W12X53'	'W21X147'	'W33X169'	'W14X90'	'W14X233'	'W10X49'
	BR	'W21X83'	'W16X50'	'W10X54'	'W21X166'	'W8X40'	'W14X90'	'W8X13'	'W8X15'	'W14X53'	'W16X26'
17-18	CG2	'W21X83'	'W14X730'	'W12X79'	'W30X116'	'W36X280'	'W33X263'	'W36X210'	'W24X84'	'W10X30'	'W14X74'
	CG3	'W18X119'	'W30X292'	'W44X230'	'W33X241'	'W12X79'	'W30X173'	'W16X77'	'W10X77'	'W18X234'	'W14X132'
	CG4	'W16X67'	'W21X62'	'W24X192'	'W40X264'	'W10X49'	'W10X49'	'W16X77'	'W36X300'	'W10X39'	'W33X291'
	CG5	'W18X65'	'W14X68'	'W12X45'	'W14X211'	'W14X61'	'W36X160'	'W12X120'	'W36X328'	'W14X61'	'W30X116'
	IB	'W18X35'	'W36X150'	'W33X169'	'W18X55'	'W40X211'	'W30X116'	'W16X67'	'W8X67'	'W18X65'	'W12X96'
	OB	'W18X35'	'W21X83'	'W21X132'	'W27X84'	'W30X90'	'W27X102'	'W12X96'	'W14X48'	'W24X103'	'W36X160'
	BR	'W10X45'	'W12X72'	'W18X50'	'W21X73'	'W33X130'	'W8X28'	'W12X65'	'W10X45'	'W14X61'	'W16X89'
	CG2	'W10X30'	'W18X40'	'W14X90'	'W30X173'	'W18X86'	'W8X31'	'W10X30'	'W12X106'	'W12X35'	'W12X87'
	CG3	'W10X33'	'W8X48'	'W18X46'	'W30X90'	'W14X48'	'W14X53'	'W10X60'	'W24X94'	'W18X46'	'W10X112'
	CG4	'W36X210'	'W18X106'	'W14X34'	'W12X53'	'W36X260'	'W16X31'	'W21X166'	'W33X241'	'W36X439'	'W27X84'
	CG5	'W10X100'	'W30X191'	'W18X40'	'W14X211'	'W8X35'	'W30X235'	'W12X252'	'W12X210'	'W12X252'	'W40X278'
	IB	'W36X150'	'W14X68'	'W18X71'	'W10X77'	'W14X132'	'W18X60'	'W16X57'	'W18X76'	'W12X58'	'W10X88'
	OB	'W16X45'	'W14X132'	'W18X97'	'W12X170'	'W18X234'	'W14X53'	'W10X68'	'W16X77'	'W30X191'	'W12X152'
	BR	'W16X45'	'W14X82'	'W6X9'	'W10X39'	'W14X132'	'W21X101'	'W10X30'	'W12X40'	'W16X45'	'W6X9'
Weight (ton)		3539.83	3066.03	3155.36	3077.17	3985.43	3106.56	2822.70	2918.67	2818.76	2994.61
Max Drift Index		_	0.75	0.82	0.79	0.80	0.98	0.86	0.85	0.99	0.96
Max Capacity Index		_	1.04	1.03	1.03	1.02	1.02	1.01	1.05	1.05	1.03
Practical Weight		3539.83	3290.15	3340.73	3077.17	4026.47	3211.41	2996.97	3052.41	3042.87	3100.23

Table 8 Sections of the best solution found for the 60-story tubed-frame for the first time for this example

Stories	Groups	Section	Stories	Groups	Section	Stories	Groups	Section
1-6	CC-A*	'W44X290'	7-12	CC-A	'W40X199'	13-18	CC-A	'W21X83'
	SC-A*	'W40X174'		SC-A	'W27X102'		SC-A	'W18X130'
	CC-B*	'W30X132'		CC-B	'W24X103'		CC-B	'W40X249'
	SC-B*	'W16X40'		SC-B	'W12X120'		SC-B	'W30X211'
	CC-C*	'W30X292'		CC-C	'W24X229'		CC-C	'W14X176'
	SC-C*	'W36X650'		SC-C	'W18X211'		SC-C	'W24X207'
	CC-D*	'W21X147'		CC-D	'W40X174'		CC-D	'W30X108'

	SC-D*	'W27X307'		SC-D	'W33X318'		SC-D	'W36X194'
	BM-A*	'W40X199'		BM-A	'W36X439'		BM-A	'W12X210'
	BM-B*	'W30X235'		BM-B	'W12X136'		BM-B	'W14X193'
	BM-C*	'W12X230'		BM-C	'W10X30'		BM-C	'W36X256'
	BM-D*	'W40X167'		BM-D	'W30X108'		BM-D	'W40X235'
	BR-D*	'W12X210'		BR-D	'W30X211'		BR-D	'W8X48'
19-24	CC-A	'W14X43'	25-30	CC-A	'W30X148'	31-36	CC-A	'W21X50'
	SC-A	'W30X108'		SC-A	'W33X291'		SC-A	'W24X162'
	CC-B	'W36X245'		CC-B	'W30X477'		CC-B	'W33X221'
	SC-B	'W12X210'		SC-B	'W14X120'		SC-B	'W24X176'
	CC-C	'W27X194'		CC-C	'W18X234'		CC-C	'W36X170'
	SC-C	'W27X235'		SC-C	'W30X108'		SC-C	'W16X100'
	CC-D	'W40X264'		BM-A	'W36X245'		BM-A	'W27X217'
	SC-D	'W21X101'		BM-B	'W8X58'		BM-B	'W18X65'
	BM-A	'W21X62'		BM-C	'W14X120'		BM-C	'W36X256'
	BM-B	'W36X328'		BR-C*	'W36X245'		BR-C	'W21X44'
	BM-C	'W18X65'		-			-	
	BM-D	'W16X50'		-			-	
	BR-D	'W14X82'		-			-	
37-42	CC-A	'W30X99'	43-48	CC-A	'W24X146'	49-54	CC-A	'W21X122'
	SC-A	'W27X217'		SC-A	'W18X175'		SC-A	'W12X65'
	CC-B	'W12X136'		CC-B	'W30X261'		CC-B	'W8X67'
	SC-B	'W12X152'		SC-B	'W14X74'		SC-B	'W18X258'
	CC-C	'W36X280'		BM-A	'W10X100'		BM-A	'W21X50'
	SC-C	'W33X130'		BM-B	'W24X62'		BM-B	'W33X118'
	BM-A	'W44X262'		BR-B*	'W30X108'		BR-B	'W12X50'
	BM-B	'W14X48'		-			-	
	BM-C	'W24X104'		-			-	
	BR-C	'W36X160'		-			-	
55-60	CC-A	'W14X53'						
	SC-A	'W10X39'						
	CC-B	'W40X249'						
	SC-B	'W18X55'			Total Weight (ton) = 6779.56			
	BM-A	'W27X114'						
	BM-B	'W14X99'						
	BR-B	'W40X321'						

a C-A, CC-B: CC-C, CC-D: Corner Columns in Tubes A, B, C and D, respectively. SC-A, SC-B, SC-C, SC-D: Side Columns in Tubes A, B, C and D, respectively, BM-A, BM-B, BM-C, BM-D: Beam Members in Tubes A, B, C and D, respectively, BR-B, BR-C, BR-D: Bracing Members in Tubes B, C and D, respectively.

Table 9 Statistical Results for the first and second example with different optimization methods

Methods	GA	PSO	ACO	SOS	ICA	WOA	ISA	FA	CSS	Literature
10 Story Frame										Ref. [31]
Best result										
Penalty method	591.34	591.36	591.35	549.51	571.03	558.05	563.19	595.71	549.24	584.93
FIFD method	598.27	581.05	578.96	550.61	568.48	560.26	559.32	576.45	543.02	---
Mean of results										
Penalty Method	832.09	866.11	862.81	654.03	808.24	766.50	733.15	765.13	645.81	---
FIFD method	739.092	740.758	755.55	627.942	732.23	771.40	655.7629	711.74	618.11	---
X-Braced 20-story frame										Ref. [35]
Best result										
Penalty method	3985.43	3066.03	3155.36	2818.76	3106.56	2994.61	2918.67	3077.17	2822.70	3539.83
FIFD method	3614.55	2993.51	3112.13	2775.39	2913.79	2921.28	2817.29	3036.29	2713.57	---
Mean of results										
Penalty method	5626.49	4683.780	4654.03	3259.86	4150.00	4125.60	3701.93	4116.53	3148.67	---
FIFD method	4351.38	3983.34	4293.17	3003.12	3675.29	3963.89	3116.21	3465.44	2803.92	----

Table 10 Statistical Results for all the examples by different penalty techniques and FIFD method

Methods	10-story Frame			
	Best Weight (ton)	Max RI	Max DI	Weight Std.
Morales and Quezada	571.25	0.98	0.96	92.68
Michalewicz and Attia	549.24	1.02	0.93	16.29
Hoffmeister and Sprave	535.63	1.08	0.91	85.36
Skalak and Shonkwiler	556.33	0.98	0.90	63.56
Joines and Houck	541.92	1.04	0.89	48.99
Smith and Tate	561.32	1.01	0.92	68.96
Bean and Hadj-Alouane	555.68	1.05	0.95	62.96
Deb	568.37	0.98	0.92	93.61
FIFD	543.02	1.00	0.96	22.36
	X-Braced Frame			
	Best Weight (ton)	Max RI	Max DI	Weight Std.
Morales and Quezada	2901.39	0.96	0.95	256.36
Michalewicz and Attia	2822.70	0.86	1.01	46.29
Hoffmeister and Sprave	2650.32	1.03	1.02	262.36
Skalak and Shonkwiler	2785.59	1.01	0.99	195.33
Joines and Houck	2765.36	1.01	1.00	165.73
Smith and Tate	2755.49	1.02	0.98	155.56
Bean and Hadj-Alouane	2786.66	0.98	1.01	120.91
Deb	2801.88	0.99	0.98	270.22
FIFD	2713.57	0.97	0.98	56.35
	60-story frame			
	Best Weight (ton)	Max RI	Max DI	Weight Std.
Morales and Quezada	7158.23	0.95	0.92	930.35
Michalewicz and Attia	6720.45	0.98	1.02	108.30
Hoffmeister and Sprave	6453.09	1.07	1.01	871.51
Skalak and Shonkwiler	7044.32	0.97	0.89	577.81
Joines and Houck	6975.29	1.01	0.89	445.14
Smith and Tate	7031.45	0.98	1.00	649.09
Bean and Hadj-Alouane	7052.44	0.99	0.97	508.46
Deb	7158.43	0.97	0.95	818.38
FIFD	6779.56	0.98	0.87	202.12