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## **OPTIMUM DESIGN OF STEEL SPACE FRAMES: TABU SEARCH VS. SIMULATED ANNEALING AND GENETIC ALGORITHMS**

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### **Abstract**

*In this paper, an algorithm is presented for the optimum design of geometrically non-linear steel space frames using tabu search. The design algorithm obtains minimum weight frames by selecting suitable sections from a standard set of steel sections such as American Institute of Steel Construction (AISC) wide-flange (W) shapes. Strength constraints of American Institute of Steel Construction—Load and Resistance Factor Design (AISC-LRFD) specification, maximum drift (lateral displacement), interstorey drift and size constraints for columns were imposed on frames. The performance of the tabu search was compared with simulated annealing and genetic algorithms for two steel space frames taken from the literature. The comparisons showed that the tabu search algorithm resulted in lighter frames.*

**Keywords:** Optimum design; tabu search; steel space frames; load and resistance factor design

### **1. Introduction**

Heuristic search algorithms such as tabu search (TS) and simulated annealing (SA) and genetic algorithms (GAs) have been used to solve discrete structural optimization problems in recent years.

All heuristic search algorithms imitate a natural phenomenon. GAs, which are applications of biological principles into computational algorithms, have been used to solve optimum structural design problems in recent years. They apply the principle of survival of the fittest into the optimization of structures. GAs are able to deal with discrete optimum design problems and do not need derivatives of functions, unlike classical optimization. GAs have been employed to solve many structural optimization problems [1-9].

SA is an application of annealing process in solids into the computational algorithms. It was originally proposed by Kirkpatrick et al. [10] for optimization problems. SA is able to solve discrete and continuous optimum structural problems. It was applied to the size and/or topological optimization of metal structures, i.e. plane frames, plane and/or space trusses subjected to static or dynamic loading using discrete and/or continuous variables [11-15]. As regards the using of SA in the optimum design of steel frames under the actual design constraints and loads of code specifications, the following articles can be considered: Huang and Arora [16], Park and Sung [17] employed SA in the optimum design of steel plane frames subjected to design constraints of American Institute of Steel Construction-Manual of steel construction: allowable stress design (AISC-ASD) [18]. Balling [19] applied SA to the optimum design of steel space frames for the design constraints of AISC-ASD [18] specification using discrete W steel sections and compared the results with the ones of branch and bound method. Degertekin [20] applied SA and GAs to the optimum design of geometrically non-linear steel space frames under the design constraints of AISC-ASD [18] and AISC-LRFD [21] specifications and compared the results of both algorithms.

TS mimics the human memory process. It was developed by Glover [22-24]. It has an artificial memory and saves information about recent search moves using tabu list which forbids recently made moves. Therefore; the probability of becoming entrapped into local optima is prevented. TS has been applied to many different fields of engineering and technology. Various applications of TS were presented by Glover and Laguna [25,26]. It was also applied to the optimum design of steel frames [27-30].

The main differences between TS and GA are summarized as: (i) TS uses an artificial memory facility in order to avoid becoming trapped in local optima, while GA has not memory facility; (ii) TS takes into account each design variable independently. On the other hand, GA considers the population pool. The main difference between HS and SA are also summarized as: (i) SA uses an acceptance probability in order to obtain new neighbor design while TS uses artificial memory. (ii) SA has probabilistic approach whereas TS uses deterministic approach.

The main objective of this paper is to introduce a TS algorithm for the optimum design of steel space frames, under the actual design constraints of code specifications AISC-LRFD [21]. The effectiveness and robustness of TS, compared to GAs and SA based algorithms, were verified using two steel space frames which exist in literature.

## 2. The Formulations of the Optimum Design Problem

The weight of frame is considered as the objective function, the standard steel sections are treated as design variables and the constraints are taken from the design codes. Therefore; the discrete optimum design problem of geometrically non-linear steel space frames can be stated as follows

$$\text{Minimize } W(x) = \sum_{k=1}^{ng} A_k \sum_{i=1}^{mk} \rho_i L_i \quad (1)$$

subjected to the stress constraints of AISC-LRFD [21], displacement and size constraints. In (1),  $mk$  is the total numbers of members in group  $k$ ,  $\rho_i$  and  $L_i$  are density and length of member  $i$ ,  $A_k$  is cross-sectional area of member group  $k$ , and  $ng$  is total numbers of groups in the frame. The design examples presented in this study are taken from author previous work [20]. Hence, the same optimum design formulations as the one of this article are used herein.

The unconstrained objective function  $\Psi(x)$  is then written as

$$\Psi(x) = W(x)[1 + kC] \quad (2)$$

where  $k$  as a penalty constant to be selected depending on the problem.  $C$  constraint violation function which is calculated as:

$$C = \sum_{j=1}^m \sum_{l=1}^{nl} C_{jl}^d + \sum_{j=1}^{ns} \sum_{i=1}^{nsc} \sum_{l=1}^{nl} C_{jil}^{\Delta} + \sum_{n=1}^{ncl} C_n^c + \sum_{i=1}^{nm} \sum_{l=1}^{nl} C_{il}^I \quad (3)$$

where  $C_{jl}^d$ ,  $C_{jil}^{\Delta}$ ,  $C_n^c$  and  $C_{il}^I$  constraint violation for maximum displacement, interstorey drift, size constraints and the interaction formulas of the AISC-LRFD [21] specification.  $m$  is the number of restricted displacements,  $nl$  is the total number of loading conditions,  $ns$  is the number of storeys in the frame,  $nsc$  is the number of columns in a storey,  $nm$  is total number

of members in the frame,  $ncl$  is the total number of columns in the frame except the ones at the bottom floor.

The penalty function may be expressed as:

$$C_i = \begin{cases} 0 & \text{if } I_i \leq 0 \\ I_i & \text{if } I_i > 0 \end{cases} \quad (4)$$

For the maximum displacement and interstorey drift constraints,  $I_{jl}^d$  and  $I_{jil}^\Delta$  are defined as:

$$I_{jl}^d = \frac{d_{jl}}{d_{ju}} - 1 \quad (5)$$

$$I_{jil}^\Delta = \frac{\Delta_{jil}}{\Delta_{ju}} - 1 \quad (6)$$

where  $\delta_{jl}$  is the displacement of the  $j$ -th degree of freedom due to loading condition  $l$ ,  $\delta_{ju}$  is its upper bound,  $\Delta_{jil}$  is interstorey drift of  $i$ -th column in the  $j$ -th storey due to loading condition  $l$ ,  $\Delta_{ju}$  is its limit.

For the size constraints,  $I_i^c$  given as follows:

$$I_i^c = \frac{d_i}{d_{iu}} - 1.0 \quad (7)$$

where  $d_i$  and  $d_{iu}$  are depths of steel sections selected for upper and lower floor columns.

The strength constraints taken from AISC-LRFD [21] are expressed in the following equations.

$$\text{for } \frac{P_u}{fP_n} \geq 0.2; I_{il}^I = \left( \frac{P_u}{fP_n} \right)_{il} + \frac{8}{9} \left( \frac{M_{ux}}{f_b M_{nx}} + \frac{M_{uy}}{f_b M_{ny}} \right)_{il} - 1.0 \quad (8)$$

$$\text{for } \frac{P_u}{fP_n} < 0.2; I_{il}^I = \left( \frac{P_u}{2fP_n} \right)_{il} + \left( \frac{M_{ux}}{f_b M_{nx}} + \frac{M_{uy}}{f_b M_{ny}} \right)_{il} - 1.0 \quad (9)$$

The terms in (8) and (9) for a member can be defined as:  $P_u$  = required axial strength (compression or tension),  $P_n$  = nominal tensile strength (compression or tension),  $M_{ux}$  = required flexural strength about the major axis,  $M_{uy}$  = required flexural strength about the minor axis,  $M_{nx}$  = nominal flexural strength about the major axis,  $M_{ny}$  = nominal flexural strength about the minor axis,  $f = f_c$  = resistance factor for compression (equal to 0.85),  $f = f_t$  = resistance factor for tension (equal to 0.90),  $f_b$  = resistance factor for flexure (equal to 0.90).

The effective length factor  $K$ , for unbraced frames were calculated from the following approximate equation [31]:

$$K = \sqrt{\frac{1.6G_A G_B + 4.0(G_A + G_B) + 7.50}{G_A + G_B + 7.50}} \quad (10)$$

where  $G_A$  and  $G_B$  are relative stiffness factors at the top and the bottom ends of column. The computation of  $\Psi(x)$  for TS requires the values of displacements and stresses in the frame. This is obtained by carrying out the non-linear analysis of space frames. In this study, an algorithm and its programming code were used developed by Levy and Spillers [32] for the analysis of geometrically non-linear space frames.

### 3. Tabu Search

TS is an optimization method which finds optimum solution by neighbourhood search in the solution space. It is based on the idea of navigating the search space by iteratively stepping from one solution to one of its neighbors, which are obtained by applying a simple local change to it [29].

A constrained optimization problem consists of constraints to be satisfied and an objective function whose minimum value is searched. Objective function is composed of design variables. Design variables are selected from a list of discrete variables that each of them is represented by a sequence number in that list.

First an initial design is generated randomly. A variable of this design is also selected randomly and various designs are obtained by changing only that variable in the range of a predetermined neighbourhood depth. For example, if the neighbourhood depth is determined as  $\pm 2$ , four different designs are obtained by exchanging the selected variable with two upper and lower variables in the sequence of the list. The best of the four designs is found (the best design is the one with the lowest objective function value). Meanwhile, the move (design variable) which determines the best design is recorded in a one-dimensional list called as 'tabu list'. The other design variables of the best design are also checked whether they are in the tabu list or not. This design is replaced with the current design even if a design variable of it is not in the tabu list and the process continues starting with the new current design. The other design variables are also selected randomly and the same process is applied to each of them. A cycle is completed when all design variables are considered. The best of the neighbourhood designs is recorded in a list with single member if it satisfies all the constraints. This list is called as 'aspiration list'. The aspiration list is updated throughout the cycles when a better feasible design is encountered. During the search process, even if all variables of a best neighbourhood design are in the tabu list, its tabu status is temporarily ignored providing that it is a better feasible design than the one in the aspiration list. These two conditions are called 'aspiration criteria'. This design is accepted as new current design and also put into the aspiration list. This design is rejected when it does not satisfy the aspiration criteria.

These processes are repeated until the terminating criterion is satisfied. In the present work, the optimization process is terminated when a predetermined total number of cycles are performed. The design in the aspiration list at the end of the last cycle is accepted as the optimum design.

Tabu list is short term memory feature, which is continually refreshed as the search explores the design space. It is a one-dimensional array whose size is kept constant during the search process. For this reason, when the tabu list is filled the oldest move at the beginning of the list is dropped and a new move is put into the end of the list.

The optimum design algorithm for steel frames using TS is graphically shown in Fig.1. In Fig. 1,  $X_c$ ,  $X_i$ ,  $X_{asp}$  denote the current design, neighbourhood designs for  $i$ -th variable of design and the design in the aspiration list, respectively.  $\psi(X_c)$ ,  $\psi(X_i)$  and  $\psi(X_{asp})$  are the corresponding objective function values.  $N$  and  $N_{max}$  are the cycle and maximum cycle number.

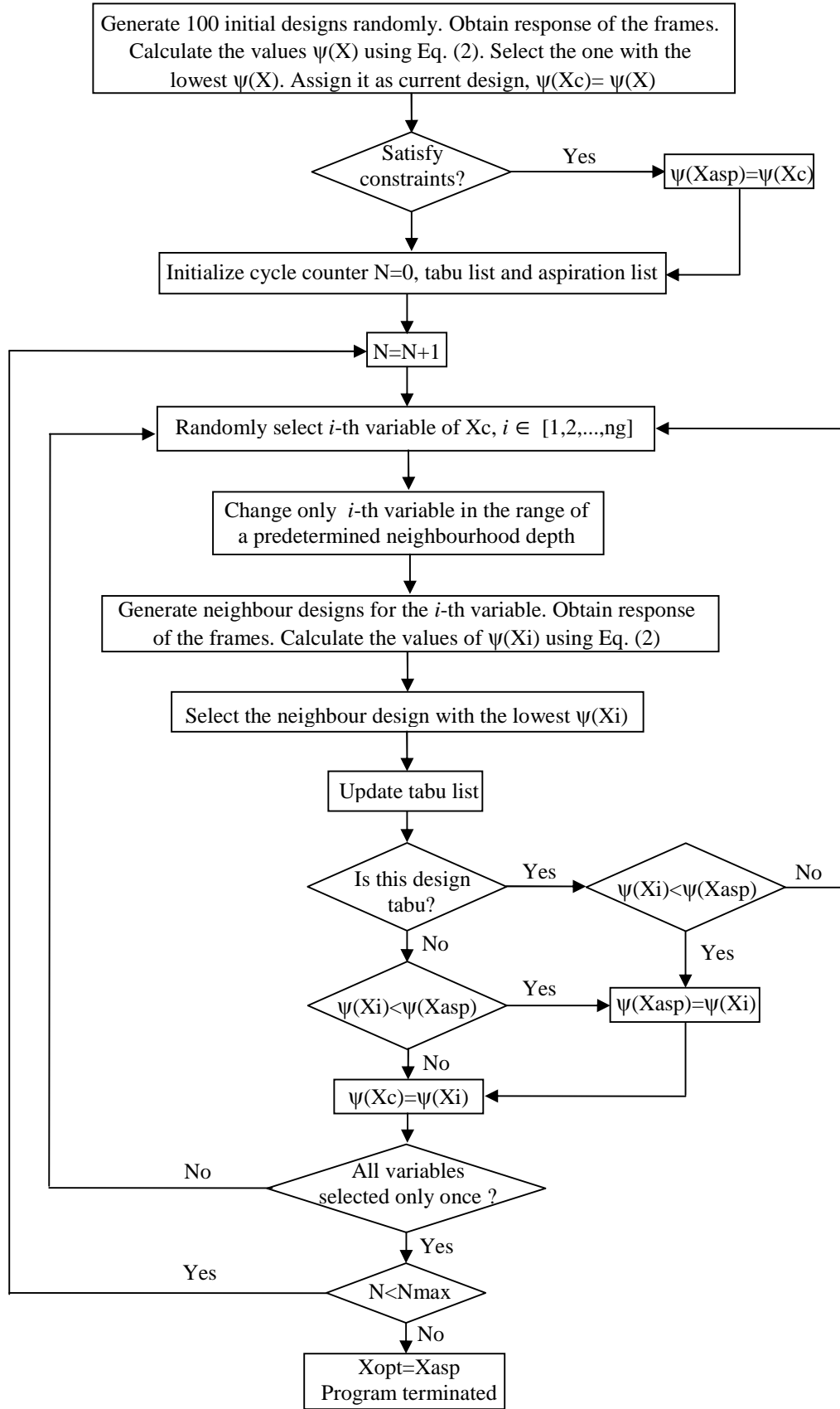


Fig. 1. Flowchart diagram for optimum design steel frames using TS algorithm

#### 4. Design Examples

In this section, TS is applied to the optimum design of two space frames. They were previously optimized using GAs and SA [20]. Therefore; material properties, design constraints and load combinations are taken the same as the ones of this article. These values are shown in tabular form in Table 1.

Table 1. Design data for steel frames

Material properties	Modulus of elasticity, $E=200$ GPa Shear modulus, $G=83$ GPa Yield stress, $f_y=248.2$ MPa Unit weight of material, $r=7850$ kg/m <sup>3</sup>
Displacement constraints	Max. drift of the top storey= $H/400$ ( $H$ : total height of the frame) Interstorey drift= $h_c/300$ ( $h_c$ : the height of considered storey)
Strength constraints	AISC-LRFD [21] interaction equations given in Eqs. (8)-(9)
Load combinations	I : $1.4D$ II : $1.2D+1.6L+0.5L_r$ III : $1.2D+1.6L_r+0.5L$ IV : $1.2D+1.3W+0.5L+0.5L_r$ ( $D$ : dead load; $L$ :live load; $L_r$ : live roof load; $W$ : wind load)

The values of 3.12 kPa for dead load ( $D$ ), 2.4 kPa for live load ( $L$ ) and roof live load ( $L_r$ ) were considered in the three design examples. Wind loading was obtained from Uniform Building Code [33] using the equation  $p = C_e C_q q_s I_w$ , where  $p$  is design wind pressure;  $C_e$  is combined height, exposure and gust factor coefficient;  $C_q$  is pressure coefficient;  $q_s$  is wind stagnation pressure; and  $I_w$  is wind importance factor. Exposure D was assumed and the values for  $C_e$  were selected depending on the frame height and exposure type. The  $C_q$  values were assigned as 0.8 and 0.5 for inward and outward faces. The value of  $q_s$  was selected as 0.785 kPa assuming a basic wind speed of 129 km/h (80 mph) and the wind importance factor was assumed to be one.

Two discrete design sets comprised 64 W sections each were used in the examples. The first one is beam section list taken from AISC-ASD [18], Part 2 which consists of suitable shapes used as beams. The boldface type sections (lighter ones) were selected starting from W36×720 to W12×19. The second one is column section list taken from the same reference, Part 3 which also consists of suitable shapes used as columns. They were selected from W14×283 to W6×15. The string length for each design variable (the section for each member group) was taken as 6 to cover all the sections in a set of 64 sections (the sequence numbers of the sections in the list vary from 0 to 63).

The following tuning parameter values were chosen for the execution of the TS algorithm: The maximum cycle number for the terminating criterion was selected as 150. It is quite important to assign an adequate value to the length of the tabu list in TS. The length should be neither so short nor so long. The short tabu list caused the search to turn around the old designs while the long list restricted the search to a small area because most of the moves were in the tabu list. Five times the number of groups was found suitable for the length of the tabu list as a result of computational experience. A value of  $\pm 3$  was found suitable for neighbourhood depth in the design examples presented in this paper. Using upper values for it did not improve the optimum design to large extent but increased computational time considerably, while the lower values for it caused local optima. In TS, a value of 0.9 was found suitable for the penalty constant  $k$  from the computational trials that the lower values for it led to local optima, while the higher ones caused premature convergence.

#### 4.1. Design of single-storey, 8 member space frame

The single-storey, 8 member space frame shown in Fig. 2 is the first example. This frame was designed by Degertekin [20] in accordance with the AISC-ASD and AISC-LRFD specifications using SA and GAs. SA yielded lighter frames together with AISC-LRFD. The members of the frame were divided into three groups organized as follows: 1-st group: the beams in  $x$ -direction, 2-nd group: the beams in  $y$ -direction, 3-rd group: the all columns. The horizontal loads due to wind act in the  $x$ -direction at each unrestrained node. The maximum top storey drift and interstorey drift were restricted to 1.3 cm.

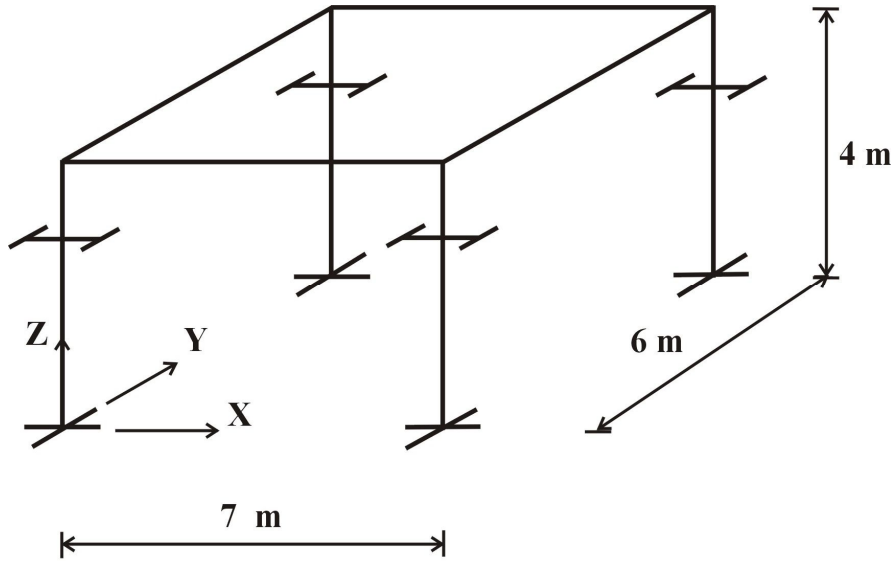


Fig. 2. Single-storey, 8-member space frame

For TS design algorithm, 10 different optimum frames were obtained generated from randomly selected 10 different initial designs and the lightest one of those was reported in Table 2. Typical convergence history of the minimum and the average frame weights for single-storey, 8-member space frame was illustrated in Fig. 3.



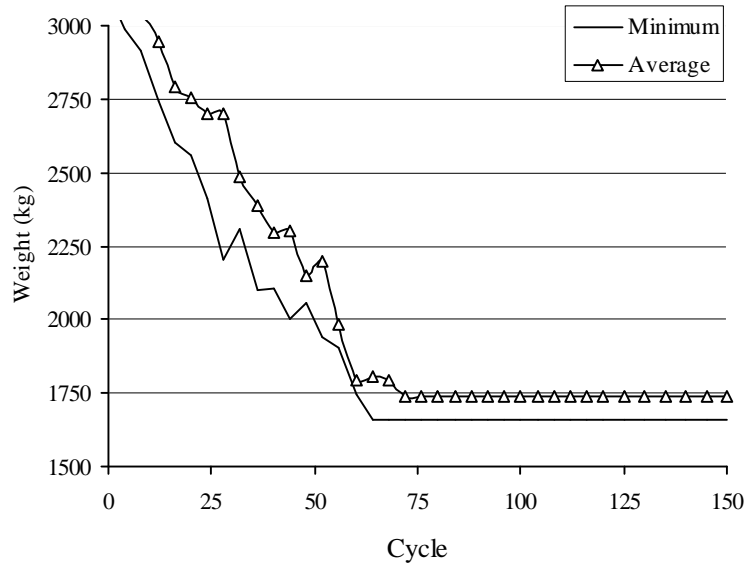


Fig. 3. Typical convergence history of single-storey, 8 member space frame

Table 2. Optimum design results of single-storey, 8-member space frame

Group no.	TS	SA	GA
	This study	Degertekin [20]	
1	W16×31	W12×30	W14×30
2	W16×26	W12×30	W14×30
3	W8×24	W8×24	W8×28
Weight (kg)	1687	1728	1830
Top storey drift (cm)	1.24	1.19	1.27
Number of analyses	10800	6120	2928
Average weight (kg)	1740	1790	1890
Standard deviation (kg)	58	43	60

The optimum design was governed by strength constraints. TS obtained 2.4% and 7.8% lighter frames than SA and GAs. The average weight of 10 runs was calculated as 1740 kg, with a standard deviation of 58 kg. Fig. 3 shows that the optimum designs obtained using TS did not change after 70 cycles and terminated search process after 10800 frame analyses, whereas SA and GAs required 6120 and 2928 frame analyses. This indicates that the number frame analyses required by TS are more than the ones of SA and GAs.

#### 4.2. Design of 4-storey, 84-member space frame

The second example is the 4-storey space frame with a square plan and side view shown in Fig. 4. The structure consists of 84 members divided into 10 groups. The groups were organized as follows: 1-st group: outer beams of 4-th storey, 2-nd group: outer beams of 3-rd, 2-nd and 1-st storeys, 3-rd group: inner beams of 4-th storey, 4-th group: inner beams of 3-rd, 2-nd and 1-st storeys, 5-th group: corner columns of 4-th storey, 6-st group: corner columns of 3-rd, 2-nd and 1-st storeys, 7-th group: outer columns of 4-th storey, 8-th group: outer

columns of 3-rd, 2-nd and 1-st storeys, 9-th group: inner columns of 4-th storey, 10-th group: inner columns of 3-rd, 2-nd and 1-st storeys.

The wind loads act in the  $x$ -direction at each node on the sides AB and CD. For the maximum and interstorey drift constraints, the values of 4.55 cm and 1.52 cm were imposed on the frame. 10 independent runs were made to optimize the frame weights and the lightest one of those was reported in Table 3. The convergence history of the minimum and the average frame weights against the number of cycle were depicted in Fig. 5.

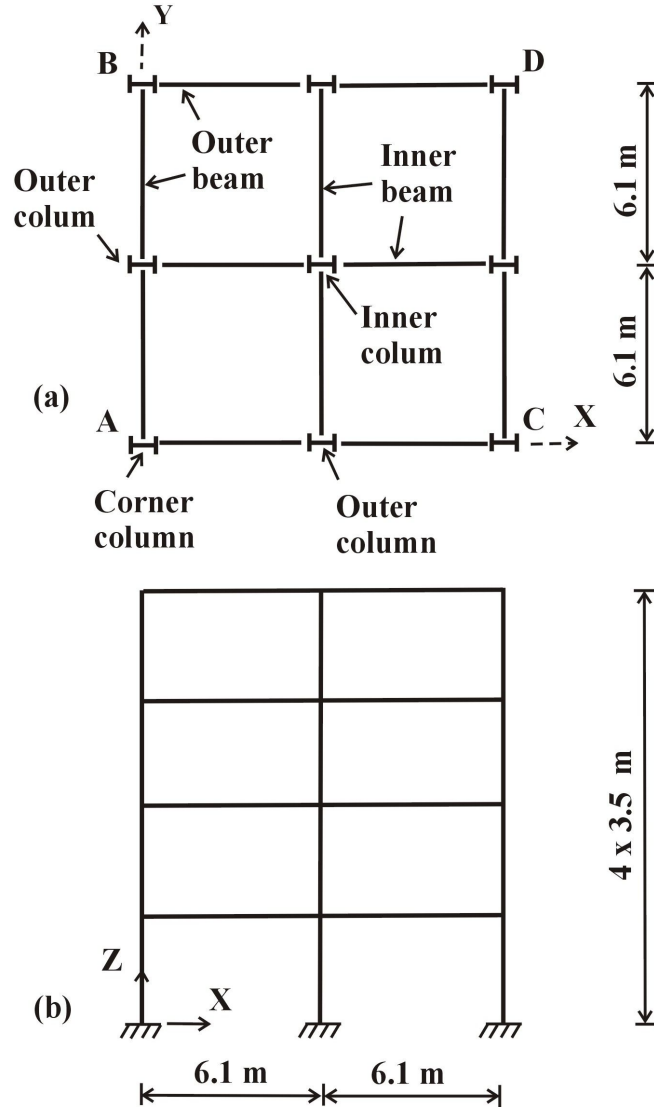


Fig. 4. Four-storey 84-member space frame: (a) plan (b) side view

As shown in Table 3, the displacement constraints were below their boundary values. This indicates that strength constraints were dominant at the optimum design. The average weight of 10 runs was calculated as 23025 kg, with a standard deviation of 408 kg. TS resulted in 3.0% and 7.0% lighter frames than the ones obtained by SA and GAs. It is also noticed that TS required 36000 frame analyses while SA and GAs required 20400 and 15520 frame analyses.

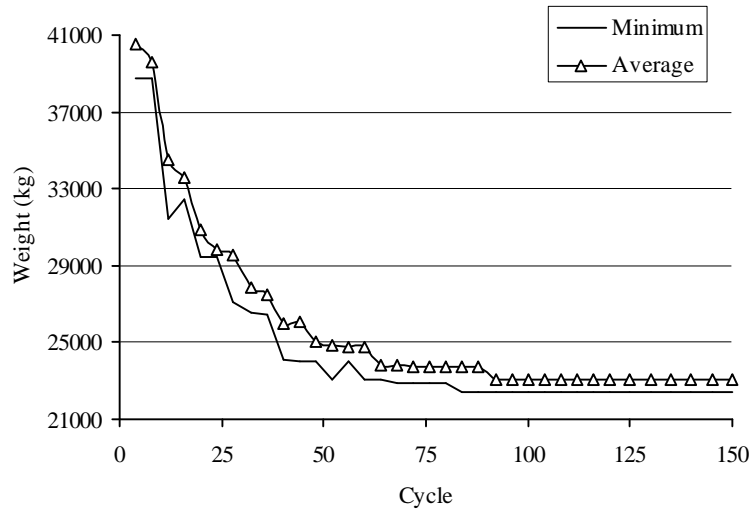


Fig. 5. Typical convergence history of 4-storey, 84-member space frame

Table 3. Optimum design results of 4-storey, 84-member space frame

Group no.	TS	SA	GA
	This study	Degertekin [20]	
1	W 16×31	W 18×35	W 18×50
2	W 16×31	W 18×35	W 18×35
3	W 18×40	W 18×35	W 18×40
4	W 18×35	W 18×35	W 18×40
5	W 8×35	W 8×31	W 10×33
6	W 14×53	W 12×40	W 12×40
7	W 8×31	W 10×39	W 8×31
8	W 8×35	W 12×45	W 10×33
9	W 8×31	W 8×28	W 8×28
10	W 14×68	W 12×58	W 14×61
Weight (kg)	22405	23105	24115
Top storey drift (cm)	4.33	4.43	4.55
Max. interstorey drift (cm)	1.30	1.52	1.52
Number of analyses	36000	20400	15520
Average weight (kg)	23025	23490	24460
Standard deviation (kg)	408	190	152

## 5. Conclusions

The benchmark examples presented in this study revealed that TS yielded lighter frames when compared to SA and GAs. TS obtained 7.0-7.8% lighter frames than GAs and also produced 2.4-3.0% lighter frames than SA. However, it should be noted that TS required more number of frame analyses than GAs and SA. The average weights of the frames were close to the best

optimum weights and standard deviations of the frames weights were also quite small in comparison with the frame weights, which were less than 5% in the design examples. These indicate that the TS algorithm is able to find optimum or near optimum. Important tuning parameters for TS, such as neighbourhood depth, the length of tabu list, the maximum cycle number and penalty constant, were determined from the computational experience and explained in Section 4.

## References

- [1] Jenkins, W.M., Towards structural optimization via the genetic algorithm. *Comput. Struct.*, 40, 1321-1327, 1991.
- [2] Jenkins, W.M., Plane frame optimum design environment based on genetic algorithm. *J. Struct. Eng.- ASCE*, 118, 3103-3112, 1992.
- [3] Rajeev, S. and Krishnamoorthy, C.S. Discrete optimization of structures using genetic algorithms. *J. Struct. Eng.- ASCE*, 118, 1233-1250, 1992.
- [4] Camp, C., Pezeshk, S. and Cao, G., Optimized design of two-dimensional structures using a genetic algorithm. *J. Struct. Eng.- ASCE*, 124, 551-559, 1998.
- [5] Pezeshk, S., Camp, C.V. and Chen, D., Design of nonlinear framed structures using genetic optimization. *J. Struct. Eng.- ASCE*, 126, 382-388, 2000.
- [6] Hayalioglu, M.S., Optimum load and resistance factor design of steel space frames using genetic algorithm. *Struct. Multidiscip. O.*, 21, 292-299, 2001.
- [7] Kaveh, A. and Kalatracji, V., Genetic algorithm for discrete-sizing optimal design of trusses using the force method. *Int. J. Numer. Meth. Eng.*, 55, 55-72, 2002.
- [8] Kaveh, A. and Kalatracji, V., Size/geometry optimization of trusses by the force method and genetic algorithm. *Z. Angew. Math. Mech.*, 84, 347-357, 2004.
- [9] Kaveh, A. and Rahami, H., Nonlinear analysis and optimal design of structures via force method and genetic algorithm. *Comput. Struct.*, 84, 770-778, 2006.
- [10] Kirkpatrick, S., Gelatt, C.D. and Vecchi, M.P., Optimization by simulated annealing. *Science*, 220, 671-680, 1983.
- [11] Bennage, W.A. and Dhingra, A.K., Single and multiobjective structural optimization in discrete-continuous variables using simulated annealing. *Int. J. Numer. Meth. Eng.* 38, 2753-2773, 1995.
- [12] Dhingra, A.K. and Bennage, W.A., Topological optimization truss structures using simulated annealing. *Eng. Optimiz.*, 24, 239-259, 1995.
- [13] Pantelidis, C.P. and Tzan, S.R., Modified iterated annealing algorithm for structural synthesis. *Adv. Eng. Softw.*, 31, 391-400, 2000.
- [14] Chen, T.Y. and Su, J.J., Efficiency improvement of simulated annealing in optimal structural designs. *Adv. Eng. Softw.*, 33, 675-680, 2002.
- [15] Hasancebi, O. and Erbatur, F., Layout optimisation of trusses using simulated annealing. *Adv. Eng. Softw.*, 33, 681-696, 2002.
- [16] Huang, M.W. and Arora, J.S., Optimal design steel structures using standard sections. *Struct. Optim.*, 14, 24-35, 1997.
- [17] Park, H.S. and Sung, C.W., Optimization of steel structures using distributed simulated annealing algorithm on a cluster of personal computers. *Comput. Struct.*, 80, 1305-1316, 2002.
- [18] American Institute of Steel Construction. *Manual of steel construction: allowable stress design*, Chicago, Illionis, 1989.
- [19] Balling, R.J., Optimal steel frame design by simulated annealing. *J. Struct. Eng.-ASCE*, 117, 1780-1795, 1991.

- [20] Degertekin, S.O., A comparison of simulated annealing and genetic algorithm for optimum design of non-linear steel space frames. *Struct. Multidiscip. O.*, 34, 347-359, 2007.
- [21] American Institute of Steel Construction. *Manual of steel construction: load and resistance factor design*, Chicago, Illionis, 1995.
- [22] Glover, F., Heuristics for integer programming using surrogate constraints, *Dec. Sci.*, 8, 156-166, 1977.
- [23] Glover, F., Tabu search-Part I, *ORSA. J. Comp.* 1, 190-206, 1989.
- [24] Glover, F., Tabu search-Part II, *ORSA J. Comp.*, 2, 4-32, 1990.
- [25] Glover, F. and Laguna, M., Tabu search, Modern heuristic techniques combinatorial problems, Osney Mead, Oxford, 1992.
- [26] Glover, F. and Laguna, M., *Tabu search*, Kluwer Academic Publishers, 1997.
- [27] Kargahi, M., Anderson, J.C. and Dessouky, M.M., Structural weight optimization of frames using tabu search. I: Optimization procedure, *J. Struct. Eng.- ASCE*, 132, 1858-1868, 2006.
- [28] Kargahi, M. and Anderson, J.C., Structural weight optimization of frames using tabu search. II: Evaluation and seismic performance, *J. Struct. Eng.- ASCE*, 132, 1869-1879, 2006.
- [29] Degertekin, S.O., Hayalioglu, M.S. and Ulker, M., Tabu Search Based Optimum Design of Geometrically Non-Linear Steel Space Frames, *Struct. Eng. Mech.*, 27, 575-588, 2007.
- [30] Degertekin, S.O., Saka, M.P. and Hayalioglu, M.S., Optimal load and resistance factor design of geometrically nonlinear steel space frames via tabu search and genetic algorithm, *Eng. Struct.*, 30, 197-205, 2008.
- [31] Dumonteil, P., Simple equations for effective length factors. *Eng. J. AISC*, 29, 111-115, 1992.
- [32] Levy, R. and Spillers, W.R., *Analysis of geometrically nonlinear structures*, Chapman and Hall, New York, 1994.
- [33] Uniform Building Code. *International Conference of Building Officials*, Whittier, California, 1997.