Multiobjective Evolutionary Design

# of Steel Structures in Tall Buildings

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This paper presents initial results of a study on the application of evolutionary multi-objective optimization methods in the design of the steel structural systems of tall buildings. In the paper, a brief overview of the state-of-the-art in evolutionary multi-objective optimization in structural engineering is provided. Next, conceptual design of steel structural systems in tall buildings is overviewed and the representations of steel structural systems used in the paper are discussed. Furthermore, Emergent Designer, a unique evolutionary design tool developed at George Mason University, is briefly described. It is an integrated research and design support tool which applies models of complex adaptive systems to represent engineering systems and to analyze design processes and their results. The paper also presents the results of several multi-objective structural design experiments conducted with Emergent Designer in which steel structural systems in tall buildings were optimized with respect to their total weight and maximum deflection (two-objective minimization problem). The goal of these experiments was to determine feasibility of evolutionary multi-objective optimization of steel structural systems of tall buildings as well as to qualitatively and quantitatively compare the results with the previous findings obtained with single-objective evolutionary optimization methods. Finally, initial research conclusions are presented as well as promising research directions.

I. Introduction

IN a vast majority of evolutionary design applications, including authors' previous studies[1], the fitness function was based on a single evaluation criterion. For example, the total weight of a steel structural system has been frequently employed as the evaluation criterion in structural engineering applications. In many cases, however, such an approach is not sufficient because other relevant aspects of designs' performance are omitted. In this paper, we extend the previous evaluation model by considering a second evaluation criterion, namely the maximum horizontal displacement of the structural system. Such a displacement is called 'sway' and is considered a good measure of deformations of a structural system under a given combination of horizontal and vertical loads. We subsequently combine both objectives in a single fitness function using a set of arbitrarily assigned weights. By considering several combinations of the weights we attempt to identify the changes of the optimal topology of a steel structural system in a tall building when the importance of each of the two objectives is modified. We also try to determine the approximate shape of the Pareto front in this two-objective performance space.

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Citation:
Kicinger, R., and Arciszewski, T. " Multiobjective evolutionary design of steel structures in tall buildings." *Proceedings of the AIAA 1st Intelligent Systems Technical Conference Chicago, IL, September 20-23, 2004*, American Institute of Aeronautics and Astronautics Press, Reston, VA, AIAA 2004-6438.

II. Background

A. Evolutionary Computation

Evolutionary algorithms (EA) have been used to solve problems in various disciplines of science and engineering[2]. They have also been applied to many structural design problems, especially those related to complex optimization issues where traditional optimization methods were generally unsatisfactory.

From the engineering perspective, evolutionary computation (EC) can be understood as a search and optimization process in which a population of solutions (designs) undergoes a process of gradual changes. This process is guided by the fitness (a measure of perceived performance) of the individual solutions as defined by the environment (objective function(s)). Hence, one of the most important issues in a successful application of EA is the choice of an adequate fitness evaluation function for a given problem. Evaluation functions provide EA with feedback about the fitness of each design in the population. This feedback is subsequently used to bias the search process in order to improve the population's average fitness.

In many problems, including structural design problems, a fitness function based on a single evaluation criterion is generally not sufficient. Hence, significant research efforts in the field of evolutionary computation have been recently focused on evolutionary multiobjective optimization (EMOO) methods. Several multiobjective evolutionary algorithms have been proposed, including *aggregating functions*[3], vector evaluated genetic algorithm (VEGA)[4], target vector approaches[5], multiobjective genetic algorithm (MOGA)[6], non-dominated sorting genetic algorithm (NSGA)[7], niched Pareto genetic algorithm (NPGA)[8], and strength Pareto evolutionary algorithm (SPEA)[9].

In this paper, we employ the simplest multiobjective evolutionary algorithms based on aggregating functions in which the objectives are multiplied by weighting coefficients representing the relative importance of the objectives.

B. Design Representations

A *representation* of an engineering design is as a computational description of an engineering system (that usually does not yet exist) expressed in terms of attributes[10]. In the most straightforward evolutionary computation representation, each gene corresponds to an attribute and represents a dimension of the search space. Each such dimension can have an appropriate set of values (discrete or continuous) that a feature represented by this dimension can take on. In the simplest case, these representations use binary genes denoting the presence, or absence, of a feature. In such representations each individual consists of a fixed-length binary string of genes, or a genotype, representing some subset of a given set of features. Often, in complex engineering applications, multi-valued attributes are more natural to use[11].

A *representation space* for an engineering design is a multidimensional space spanned over attributes that are used to describe an engineering design[10]. Attributes can be *symbolic* (when they take values from an unordered or partially ordered set) or *numerical* (when they take numerical values representing quantities or measurements). Symbolic attributes that take values from an unordered set are called nominal attributes; when they take values from a partially ordered set, they are called structured. *Design concepts* are typically described in terms of symbolic attributes. Numerical attributes are used for a detailed description of a design.

Appropriate representation of an engineering system is one of the most crucial elements of evolutionary design. The process of creating an efficient and adequate representation of an engineering system for evolutionary design is complicated and involves elements of both science and art. One has to take into account not only important aspects of understanding traditional modeling of an engineering system, but also relevant computational issues that include search efficiency, scalability, and mapping between a search space (genotypic space) and a space of actual designs (phenotypic space).

C. Evolutionary Optimization in Structural Engineering

Evolutionary methods have relatively long history in structural design. Initial applications considered sizing and shape optimization of relatively simple structural systems, including trusses[12,13] and frames[14]. Later, more complex structural design problems were investigated including topology optimization of discrete-member trusses[15], topology optimization of truss structures in pylons[16], and topology, shape, and sizing optimization of truss structures[17]. Topological optimum design of steel structural systems in tall buildings was initially studied in Ref. 18,19 and later extended in Ref. 1.

Several applications of multiobjective evolutionary methods have been also conducted. Several variations of the original VEGA have been proposed and applied to the conceptual design of airframes[20]. The weighted min-max algorithm (target vector approach) has been used in Ref. 21 to optimize a 10-bar plane truss, and in Ref. 22 and Ref. 23 to optimize I-beams and truss designs. MOGA has been used in many engineering design applications including gas turbine controller[24] and supersonic wings[25,26]. A variation of MOGA (called MGA) was applied to conceptual design of office buildings[27]. NSGA-II has been recently applied to a topological optimum design problem[28]. In this approach, both the weight and the maximal displacement of a cantilever plate were minimized. A hybrid approach, NSGA-II and a hill climber, was employed to solve several engineering shape optimization problems[29].

Comprehensive surveys of various evolutionary multiobjective optimization methods, including detailed discussion on their strengths and weaknesses can be found in Ref. 5,30-34.

D. Conceptual Design of Steel Structural Systems in Tall Buildings

Steel skeleton structures in tall buildings are considered ones of the most complicated structures designed and built. Their conceptual and physical complexity can only be compared to such complex structural systems as, for example, large span bridges or large span space structures. Usually, steel structural systems in tall buildings are designed as a system of vertical members called columns, horizontal members called beams, and various diagonal members called wind bracings, since they are added to columns and beams to increase the flexural rigidity of the entire system and that is driven mostly by stiffness requirements related to wind forces.

Skeleton structures are designed to provide a structural support for tall buildings. They have to satisfy numerous requirements regarding the building's stability, transfer of loads, including gravity, wind and earthquake loads, deformations, vibrations, etc. For this reason, the design of structural systems in tall buildings requires the analysis of their behavior under various combinations of loading and the determination of an optimal configuration of structural members. It is difficult, complex, and still not fully understood domain of structural engineering, particularly as the generation/development of novel structural concepts is concerned.

III. Evolutionary Multiobjective Structural Design

A. Topological Structural Design

In this paper, multiobjective topological optimum design of steel structural systems in tall buildings is investigated. It is considered as a two-stage process. In the first stage, an evolutionary algorithm produces a design concept, which is understood here as an abstract description of a future structural system represented in terms of symbolic attributes. It identifies the configuration of the following members of a structural system: wind bracings, beams, and column supports. The configuration of columns is assumed constant (the location and nature of columns do not change) and is not evolved. In the second stage, sizing optimization of all structural members, including wind bracings, beams, and columns, is conducted for the design configuration determined in the first stage.

The sizing optimization is conducted by SODA. It is a commercial computer program for the analysis of internal forces, dimensioning and numerical optimization of steel structural systems. In the project, a modified SODA program developed by the Waterloo Systems in Waterloo, Ontario, Canada, has been used. The optimization method used in SODA is described in Ref. 35. In the structural analysis conducted by SODA, dead, live, and wind loads as well as their combinations are considered. The structural elements are designed using several groups of sections for beams, columns, and bracings. In the performed experiments the first order analysis was used (P-Delta effects were not considered).

As stated earlier, in this paper a simple multiobjective evolutionary algorithm based on aggregating functions was employed. The two performance measures considered in the design experiments included the total weight of the steel structural system and its maximum horizontal displacement. The total weight of a steel structure provides a good estimate of the cost of a steel structural system while the maximum horizontal displacement estimates its stiffness. Each of the two performance measures can be used as an objective with respect to which the produced design concepts are optimized (minimized). However, the two objectives are usually conflicting. The reduction of the weight of a steel structure increases its maximum horizontal displacement (and thus reduces its stiffness) and vice versa. The perceived importance of each of the two objectives was determined by applying appropriate weighting coefficients.

B. Emergent Designer

Multiobjective evolutionary optimization experiments reported in this paper were conducted using Emergent Designer, an experimental research and design tool developed at George Mason University. It is an integrated Java-based system intended for conducting design experiments in the area of structural design and for the analysis of their results. It implements state-of-the-art representations supporting generation of novel design concepts and efficient mechanisms for their subsequent optimization at the topology and member sizing level. It also implements advanced methods, models, and tools from statistics and from the linear as well as nonlinear time series analysis to conduct the analysis of the design processes. The system has ten major components:

1. Problem Definition Component
2. Representation and Decomposition Component
3. Concept Generation and Optimization Component
4. Evaluation and Simulation Component
5. Basic Statistical Analysis Component
6. Basic Dynamical Systems Analysis Component
7. Advanced Statistical Analysis Component
8. Advanced Time Series Analysis Component
9. Visualization Component
10. Report Generation Component

A detailed description of the system can be found in Ref. 36.

C. Representations of Steel Structural Systems in Tall Buildings

In the design experiments reported in this paper, a structural system of a tall building is considered as a system of identical parallel planar transverse structures, which are the subject of design. The representation space has been developed using the concept of division of the structural grid of the building (the system of vertical and horizontal lines of columns and beams, respectively) into units, or cells. A *cell* can be described as a part of the structural grid contained within the adjacent vertical and horizontal grid lines[19].

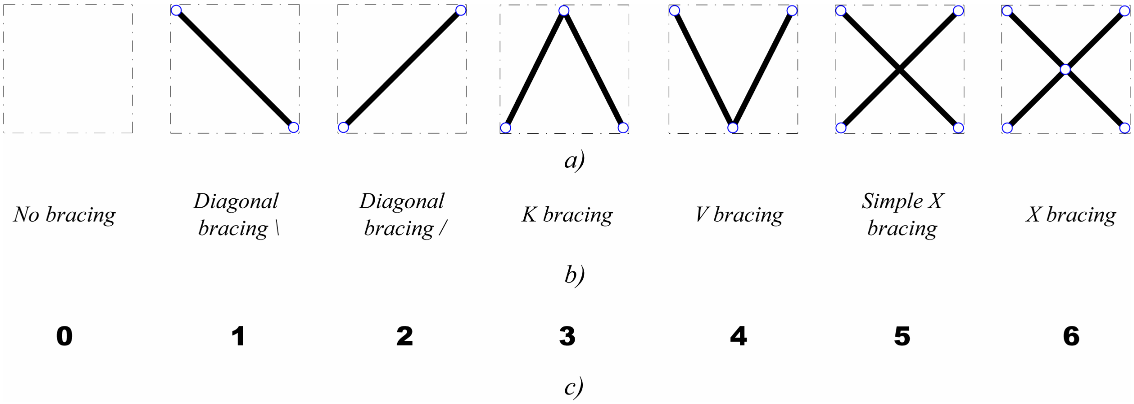


Figure 1. a) Phenotypic, b) symbolic, c) genotypic values of attributes representing wind bracing.

Representations of steel structural systems in tall buildings encoded the following types of structural members: bracings, beams, and supports. Figure 1 shows the values of attributes representing bracing elements in a steel structural system at the phenotypic, symbolic, and genotypic level. Each such attribute can have up to seven symbolic values (see Figure 1b)) encoding various types of bracings (no bracing, diagonal bracing \, diagonal bracing /, K bracing, V bracing, simple X bracing, and X bracing). Their phenotypic, or design, representation is presented in Figure 1a). Figure 1c) shows genotypic values of the attributes representing bracing elements. Each such attribute has 7 possible values encoded as integers 0 to 6.

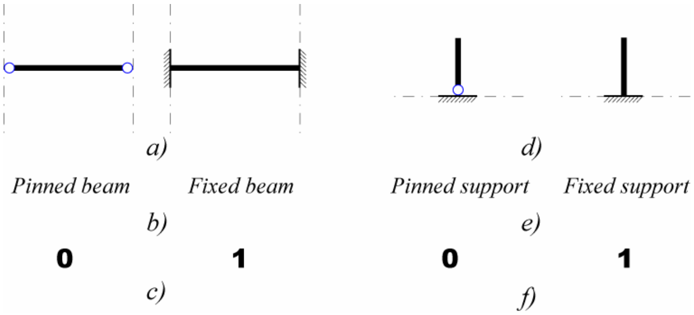


Figure 2. a) Phenotypic, b) symbolic, c) genotypic values of attributes representing beams and d) phenotypic, e) symbolic, f) genotypic values of attributes representing supports.

In Figure 2 values of attributes representing beams and supports are presented. Each attribute representing a beam in a steel structural system had two symbolic values (binary attributes) (see Figure 2c)) encoding two types of beams (a pinned beam and a fixed beam) (see Figure 2a) and Figure 2b)). Similarly, each attribute representing a support in a steel structural system was binary (see Figure 2f)) and encoded two types of supports (a pinned support, and a fixed support) (see Figure 2d) and Figure 2e)).

The actual genotypic representation, or genome, that was manipulated by an evolutionary algorithm, was encoded as a string of integer values. In the design experiments reported in this paper, fixed-length genomes were used as representations of steel structural systems. The length of a genome used in a given design situation depended on the number of cells in the structural system being considered, and that is obviously related to the number of stories and the number of bays in a tall building.

IV. Experimental Design

Initial multiobjective design experiments reported in this paper were aimed to determine how the optimal topologies of steel structural systems in tall buildings change when the perceived importance of each of the two objectives, i.e. the total weight of the structural system and its maximum horizontal displacement, is varied. This goal has been realized through the analysis of the results of a number of design experiments in which several combinations of weighting coefficients were used to determine the importance of the two objectives.

Table 1. Problem parameters and their values.

Problem Parameter	*Value(s)*
Number of stories	36
Number of bays	3
Bay width	20 feet (6.01 m)
Story height	14 feet (4.27 m)
Distance between transverse systems	20 feet (6.01 m)
Types of bracing elements	No, Diagonal \, Diagonal /, K, V, Simple X, and X
Types of beam elements	Pinned-Pinned, and Fixed-Fixed
Types of column elements	Fixed-Fixed (only)
Types of supports	Pinned, and Fixed

D. Problem Parameters

The parameters of the design problem and their values are presented in Table 1. It shows that 36-story buildings with 3 bays were studied here. The height of each story was equal to 14 ft (4.27 m) while the bay widths were equal to 20 ft (6.01 m).

As discussed in the previous section, 7 types of wind bracing elements (see Figure 1), 2 types of beams, and 2 types of supports were considered (see Figure 2).

In the structural analysis conducted by SODA, dead, live, and wind loads were considered. The magnitudes of the loads used in the design experiments reported in this paper are provided in Table 2. Five load combinations were considered, following the design specifications for steel, concrete, and composite structures in tall buildings given in Ref. 37. They included the following combinations of loads:

Table 2. Magnitudes of dead, live, and wind loads.

Load Parameter	*Value(s)*
Dead load magnitude	50 psf (2.39 kN/m2)
Live load magnitude:	
- building	100 psf (4.78 kN/m2)
- roof	30 psf (1.43 kN/m2)
Wind load:	
- Wind speed	100 mph (160.9 km/h)
- Wind importance factor	1.0
- Wind exposure category	C

- Dead + Live
- 0.75(Dead + Live + Wind)
- 0.75(Dead + Live – Wind)
- 0.75(Dead + Wind)
- 0.75(Dead – Wind)

The negative sign placed in front of the wind loads indicates that the wind forces considered in a given load combination act in the opposite direction, i.e. wind pressure is replaced by wind suction and vice versa, when compared to the case when the plus sign is used.

Table 3 . Evolutionary computation parameters and their values.

EA Parameter	*Value(s)*
EA	ES
Pop. sizes (parent, offspring)	(12,60)
Generational model	Overlapping ES($\mu+\lambda$)
Selection (parent, survival)	(uniform stochastic, truncation)
Mutation rate	0.05, 0.1, 0.3, or 0.5
Crossover (type, rate)	(uniform, 0.0), (uniform, 0.2), (uniform, 0.5)
Genome length	220 genes
Fitness	Weighted average involving two objectives: - the total weight of the structural system - the maximum horizontal displacement of the structural system ('sway')
Weighting coefficients	0.0, 0.2, 0.4, 0.6, 0.8, or 1.0
Initialization method	Random, or arbitrarily selected initial parents (see Appendix)
Termination criterion	1,000 fitness evaluations (short-term) 10,000 fitness evaluations (long-term)
Number of runs	5 (in each experiment)

E. Evolutionary Computation Parameters

In Table 3 evolutionary computation parameters and their values which were used in the design experiments are presented. In the experiments, evolution strategies (ES) were employed to perform evolutionary optimization processes. The overlapping generational model was used, i.e. ES($\mu+\lambda$), which means that the survival selection acted on a combined population of parents and offspring.

Two groups of evolutionary optimization experiments were conducted: short-term experiments and long-term experiments. The short-term optimization runs were terminated after the generation of 1,000 designs. On the other hand, the long-term processes were significantly longer and involved 10,000 structural designs.

As discussed earlier, the fitness of a design concept was calculated as a weighted average of the normalized total weight of a structural system and the related normalized maximum horizontal displacement. 6 combinations of weighting coefficients (shown in Table 3) were used in the multiobjective design experiments, including $0.0 \cdot W + 1.0 \cdot D$, $0.2 \cdot W + 0.8 \cdot D$, etc., where W denotes the total weight of the structural system and D its maximum horizontal displacement.

An exhaustive parameter search involving 12 combinations of mutation and crossover rates (see Table 3) was conducted during the short-term evolutionary optimization processes. It was aimed to identify the 'optimal' rates that generated the best evolutionary optimization progress. The experiments were repeated 5 times for each combination of parameter values using a different value of a random seed each time. The optimal values were subsequently used in the long-term evolutionary optimization experiments.

Two methods of initialization of evolutionary optimization processes were employed. First, the ES was started with randomly generated design concept, as it is traditionally done in EC. Second, a set of 12 known design concepts (see Appendix) was used as initial parents. The results of both initialization methods were later compared.

Each design concept was represented by a fixed-length genome consisting of 220 genes. 108 genes encoded attributes defining types of wind bracing elements. These genes had 7 possible values representing 7 types of wind bracing elements. 108 genes encoded attributes representing beams. These genes had binary values. Finally, 4 genes encoded types of supports and also had binary values.

The experimental results are presented in the following section.

V. Experimental Results

The sensitivity analyses conducted during the short-term optimization processes revealed that the best evolutionary optimization progress was achieved for the mutation rate equal to 0.1 and the crossover rate equal to 0.2. It was also discovered that the mutation rate has much higher impact of the fitness of produced design concepts than the crossover rate. Hence, these 'optimal' values were subsequently used in the long-term multiobjective evolutionary optimization experiments.

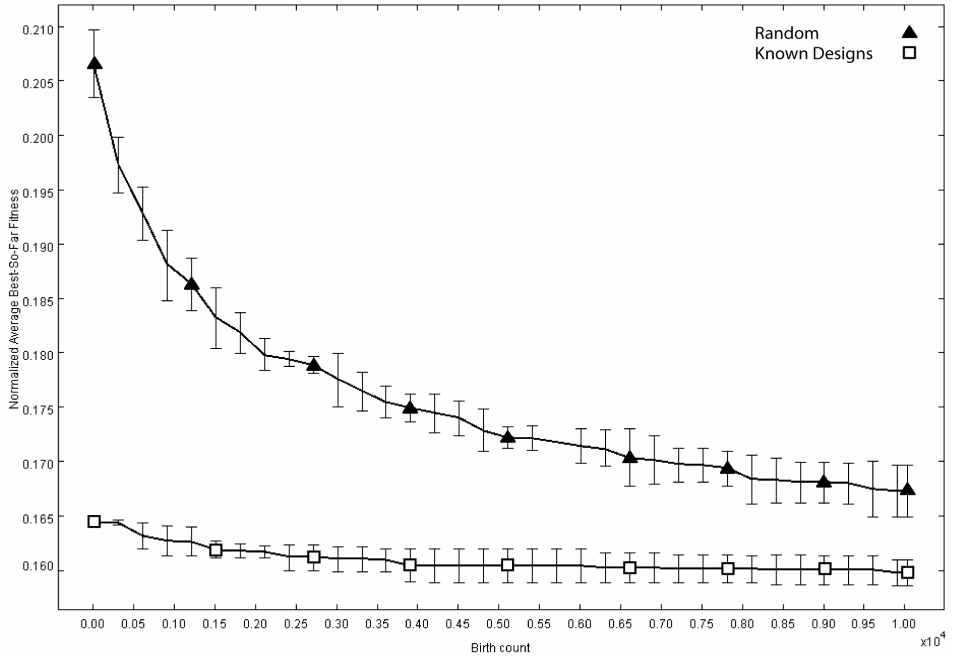


Figure 3. Comparison of the normalized average best-so-far fitness obtained in the multiobjective evolutionary optimization experiments with randomly initialized parents (Random) and known designs used as initial parents (Known Designs) (here the fitness was calculated using the formula: 0.2W+0.8D).

A. Impact of the Initialization Method

Figure 3 shows the normalized average best-so-far fitness curves obtained in two multi-objective evolutionary optimization experiments with randomly initialized parents and known designs used as initial parents. The vertical lines represent 95% confidence intervals calculated using the modified Johnson's t test. In this case, the fitness of the design concepts was calculated using the following coefficients: 0.2 for the total weight and 0.8 for the maximum displacement. Figure 3 clearly shows that in this case the evolutionary processes initialized with known design concepts outperformed the ones initialized randomly. However, evolutionary optimization processes initialized with known parents did not always produce superior results.

Figure 4 shows the normalized average best-so-far curves for another combination of weighting coefficients. Here, both multiobjective evolutionary design processes produced similar results. In general, the following pattern has been observed in the conducted experiments. For low values of the weighting coefficient associated with the total weight of the steel structural system, the evolutionary optimization processes initialized with known design concepts significantly outperformed the ones initialized randomly. However, when the value of this coefficient was increased (and the value of the coefficient associated with the maximum displacement was decreased) then both initialization methods produced similar results. In some cases, random initialization slightly outperformed the initialization with known designs.

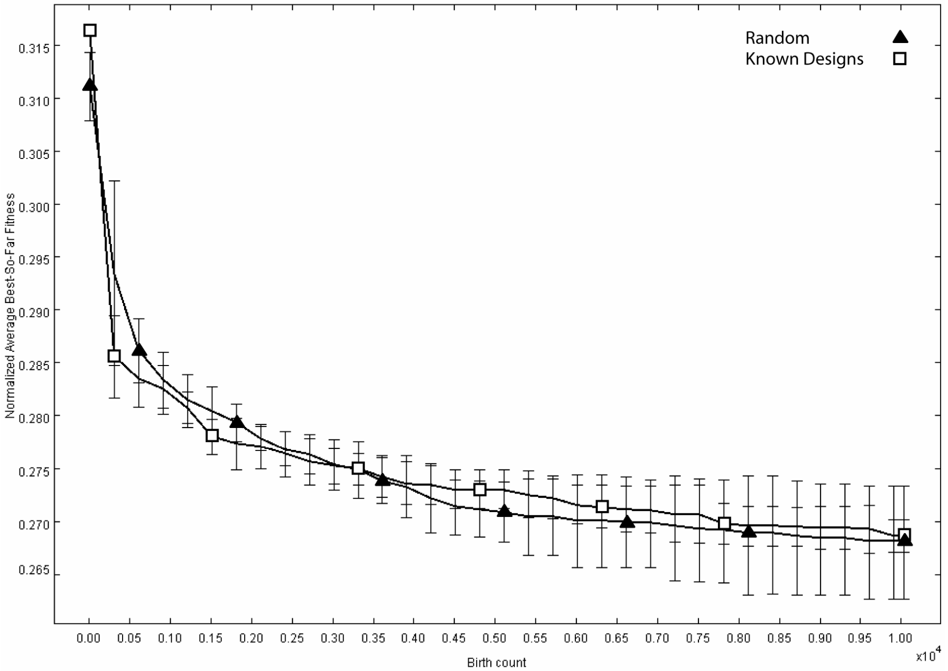


Figure 4. Comparison of the normalized average best-so-far fitness obtained in the multiobjective evolutionary optimization experiments with randomly initialized parents (Random) and known designs used as initial parents (Known Designs) (here the fitness was calculated using the formula: 0.6W+0.4D).

B. Approximate Shape of the Pareto Front

The best design concepts of steel structural systems produced in all design experiments involving various combinations of weighting coefficients were analyzed with respect to the values of both objectives. The results of this analysis are presented in Figure 5. It shows an approximate shape of the Pareto front spanned over the performance space formed by the total weight of the structural system and its maximum horizontal displacement.

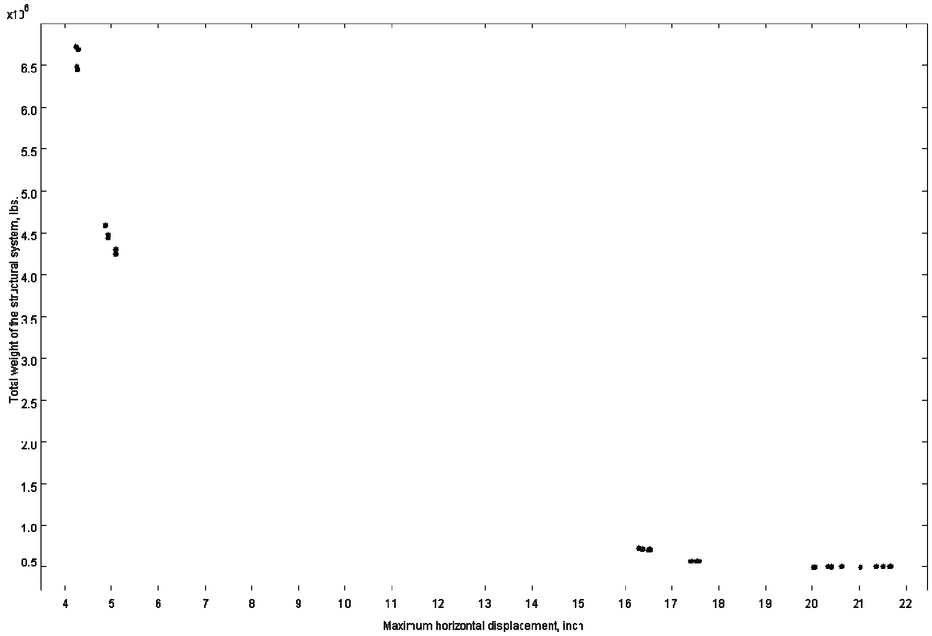


Figure 5. Approximate shape of the Pareto front in the performance space spanned over of the total weight of the steel structural system and its maximum horizontal displacement.

It clearly shows that the total weight of the optimal structural designs varies from about 500,000 lbs. to more than 6,500,000 lbs. At the same time, the maximum horizontal displacements of the structural systems range from 4 inches to almost 22 inches. Figure 5 also shows that there is a strong trade-off between the two objectives.

C. Optimal Topologies of Steel Structural Systems

The best design concepts shown in Figure 5 were also analyzed qualitatively for changes in their topologies occurring when the importance of each of the two objectives was modified. Figure 6 shows the topologies of the structural systems associated with approximate Pareto front which was discussed in the previous section.

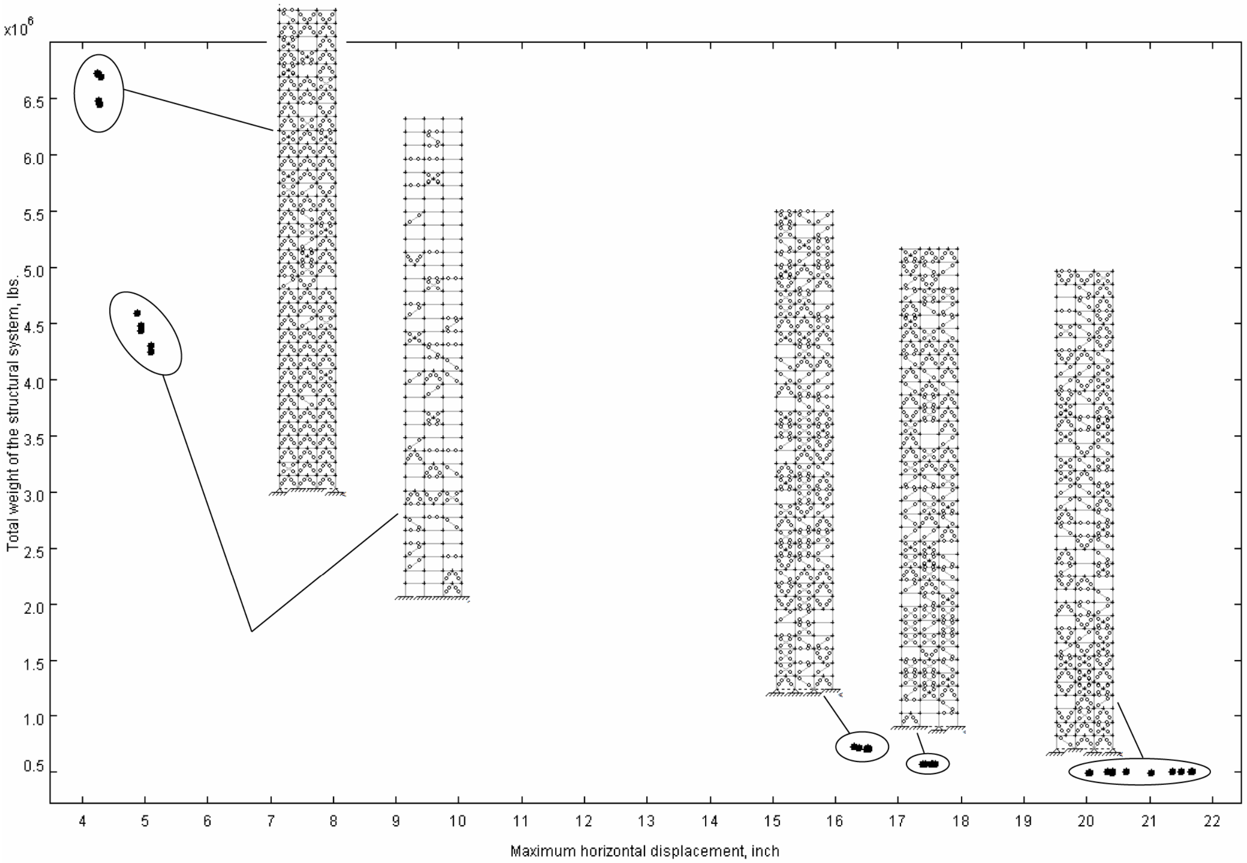


Figure 6. Topologies of the optimal structural systems associated with the approximate Pareto front.

Figure 6 clearly shows that there are significant qualitative differences among the topologies of the structural systems located in various parts of the Pareto front. The leftmost design in Figure 6 corresponding to the region of the Pareto front with the smallest horizontal displacements and the largest total weight exhibits dramatically different structural shaping pattern than the second design shown to the left. In the former case, a fairly uniform pattern of K bracings can be identified with occasional occurrences of X bracings. In the latter case, wind bracing elements appear only occasionally and the stiffness of the structural system is provided by the increased cross-sections of beams and columns. The three rightmost designs in Figure 6 are again different than the previously described designs. Here, combinations of relatively large numbers of X and K bracings can be identified. The topologies of the three rightmost design concepts are much more similar than the leftmost designs.

When we compare the design concepts shown in Figure 6 to the ones generated in the design experiments in which the total weight of the structural system was used as the only objective and the maximum horizontal displacement was imposed as a constraint (see Figure 7), we can identify significant qualitative and quantitative differences. The designs shown in Figure 7 are almost 50% heavier than the rightmost designs shown in Figure 6. At the same time they exhibit substantially smaller (also by about 50%) horizontal displacements.

The quantitative characteristics of the structural systems shown in Figure 7, i.e. their total weights and the maximum horizontal displacements, show that these designs are located close to the central region of the Pareto front.

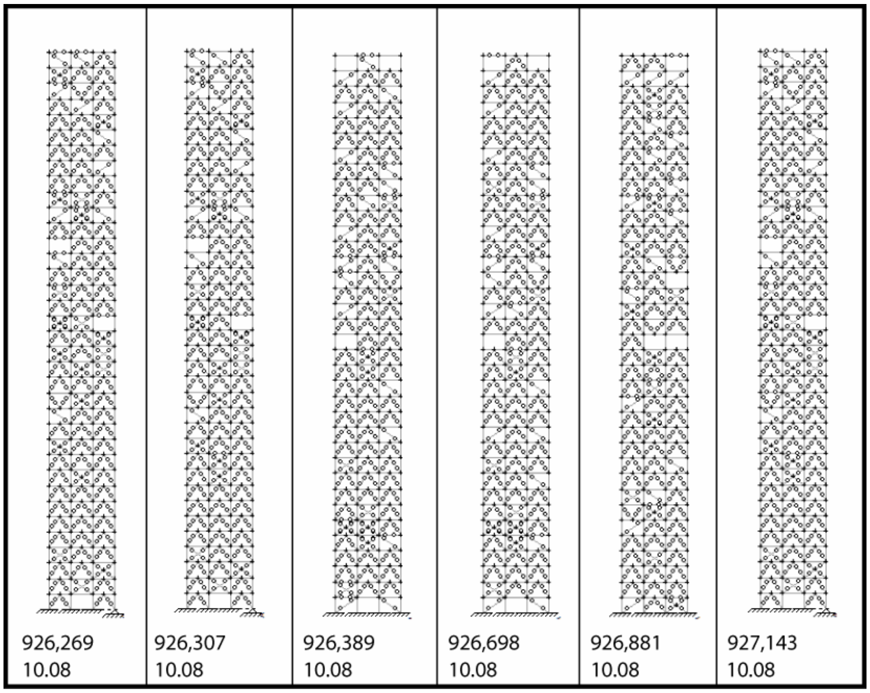


Figure 7. Topologies of the optimal structural systems generated in the single-objective design experiments.

VI. Conclusion

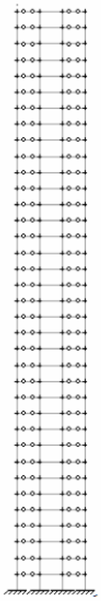
Research reported in this paper is the continuation of the previous work on evolutionary optimization of steel structural systems in tall buildings. Here, the preliminary results are provided concerning the use of a simple multiobjective evolutionary algorithm. The initial findings are encouraging and provide new insights and broader understanding of this complex structural design problem.

The conducted research will be continued. Specifically, more advanced multiobjective evolutionary algorithms will be implemented and applied to this complex design problem. Also, the shape of the Pareto front in this two-objective design performance space will be further investigated.

Appendix

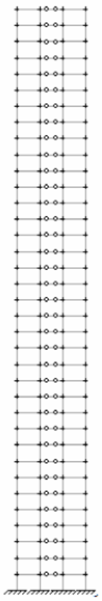
In this appendix, a set of 12 design concepts of steel structural systems in tall building is presented. These designs were used as initial parents in the design experiments reported in this paper. The two values placed below each design represent the total weight of the structural system (top) and its maximum horizontal displacement (bottom) calculated using the first-order structural analysis.

Design No.1



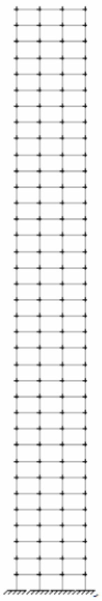
3,543,720
48.6806

Design No.2



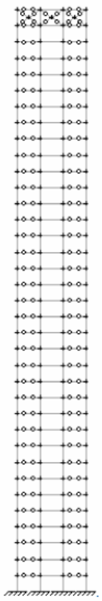
3,543,720
24.8265

Design No.3



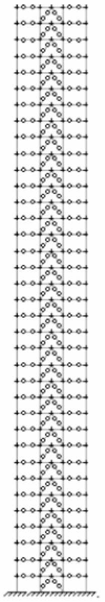
1,397,882
9.9771

Design No.4



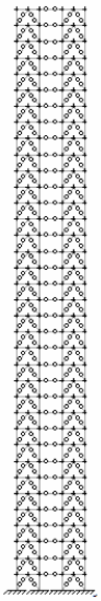
3,668,021
20.8332

Design No.5



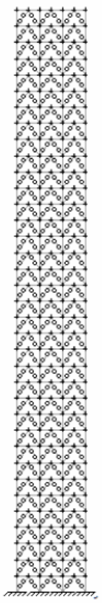
4,594,901
43.9445

Design No.6



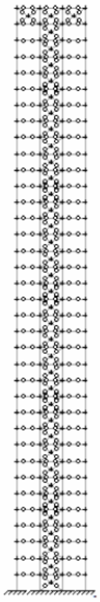
5.646,082
22.368

Design No.7



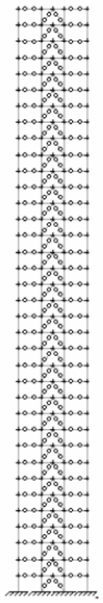
1,015,753
9.8546

Design No.8



5,118,195
18.7918

Design No.9



4,594,901
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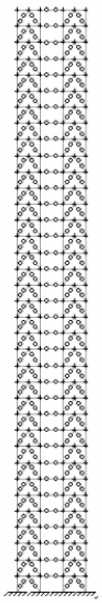
Design No.10



5,646,082
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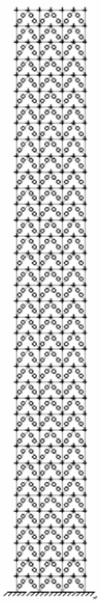
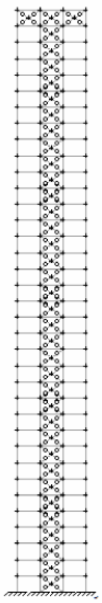
Design No.11



1,040,868
10.0713

Design No.12



1,272,675
10.0812

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