

Evolutionary Design of Steel Structures in Tall Buildings

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Abstract: This paper presents results of a study on evolutionary computation in the design of the steel structural systems of tall buildings. It describes results of extensive research on both short-term (up to a few hundred generations) and long-term evolutionary design processes (at least a few thousand generations). The experiments were conducted with Inventor 2001, an evolutionary design support tool developed at George Mason University, for generating conceptual and detailed designs of steel structural systems in tall buildings. First, the paper discusses conceptual design of steel structural systems in tall buildings and briefly introduces Inventor 2001 as well as its design representation and evolutionary computation characteristics. Next, it provides the results obtained from systematic parametric design experiments conducted with Inventor 2001. The objective of these experiments was to qualitatively and quantitatively investigate evolution of steel structural systems of tall buildings during a multistage evolutionary design process as well as the influence of various evolutionary computation parameters. Mutation and crossover rates, population size, the length of the evolutionary processes, and the importance of a symmetry requirement have been analyzed and results produced. Emergence of structural shaping patterns has been also studied and several interesting patterns found in the evolutionary design process. Finally, research conclusions are presented as well as recommendations for further research and development of evolutionary design support tools.

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Introduction

In the past 15 years, there has been a growing interest in using evolutionary methods to conduct numerical optimization of structural systems and to produce novel concepts of such systems. The notion of evolution has its roots in biology. However, the concept of evolution is well known in engineering. For example, in the traditional design process, a designer usually evolves the design concepts over a period of time. Also, the notion of evolution is the foundation of an emerging design paradigm, called “evolutionary design.” It is a specific type of engineering design process in which a large number of design concepts is produced using an evolutionary computation (EC) mechanism. Evolutionary design can be entirely conducted on a computer, and in this way it can simulate and expand the traditional manual evolution of design

concepts in terms of acquiring knowledge and making the design process more holistic and creative. Therefore, evolutionary design opens new ways for the generation of structural design concepts that might not have been previously even considered.

Past progress in engineering design has usually been incremental. Sometimes, however, a paradigm change or “gestalt shift” occurs, bringing new understanding, models, methods, and tools to a given engineering domain. It is the writers’ opinion that such a paradigm change is occurring now and that an explosion of evolutionary computation applications in all engineering domains can be observed. Evolutionary design support tools allow researchers and engineers to produce thousands, or even hundreds of thousands, of designs based on feasible design concepts in a relatively short period of time. This is not merely a random search process; it is an evolutionary guided generation of designs. Moreover, it expands the traditional scope of design. First, when the evolutionary design process is conducted, a large collection of design points in a given representation space is identified and a so-called global picture of a given design situation emerges (Arciszewski et al. 2003), which is equivalent to acquiring a significant amount of design knowledge. Second, it can lead to the discovery of novel designs.

The objective of the experiments described in this paper is to investigate several evolutionary computation parameters and their impact on the evolution of structural systems in tall buildings. The experiments can be described as testing the effects of “turning the knobs” of evolutionary computation during the process of evolutionary design. The writers have also studied emerging structural configuration patterns in the evolutionary design process in terms of novel structures and substructures. Finally, research conclusions are presented as well as recommendations for further research.

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Background

An extensive literature review is provided in Kicinger et al. (2005). In this section, the writers provide only a short overview of the problems related to the design of steel structural systems in tall buildings and introduce an evolutionary design support tool developed at George Mason University, called "Inventor 2001."

Design of Structural Systems in Tall Buildings

Design of structural systems of tall buildings is one of the most complex and time-consuming tasks for structural engineers. In this paper it is considered as a two-stage process. The first stage, usually called "conceptual design," produces a design concept, or a class of design concepts. By this term, an abstract description of a future structural system is understood, and it is provided in terms of qualitative/symbolic attributes. It identifies the configuration of a structural system, the nature of connections, materials, etc. The second stage, called "detailed or numerical design," produces a detailed design, and it involves structural analysis, dimensioning, and numerical optimization. One of the most difficult and important parts of the design process is the determination of an appropriate configuration of a structural system for a given building. In terms of novelty and weight of a structural system, the optimization of its configuration is much more important than the final numerical optimization of the individual structural members, or even of an entire structural system if an incorrect design concept is selected. However, because of the complexity of this problem, usually a structural system configuration is selected considering only very few design concepts, which are not necessarily optimal for a given building (Mustafa and Arciszewski 1992). In the case of the reported experiments, the entire design process was simulated on a computer. Evolutionary computation was used to generate the design concepts, while detailed designs based on these concepts were produced by the structural optimization design and analysis (*SODA*) software package. *SODA* 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 Waterloo Systems in Waterloo, Ontario, Canada, has been used. The optimization method used in *SODA* is described in Grierson and Cameron (1989). 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, i.e., 61 groups of sections for each structural system [using the properties of the standard shapes from the American Institute of Steel Construction (AISC) *Manual of Steel Construction* (AISC 1989)]. In *SODA*, the structural analysis can be conducted using either first-order or P - Δ analysis. However, in the performed experiments only first-order analysis was used.

Inventor 2001

Researchers at George Mason University in the Information Technology and Engineering School have developed an experimental evolutionary computation support tool, Inventor 2001, for evolving structural systems designs for tall buildings (Murawski et al. 2001). It produces both the design concepts and detailed designs. The system has six major components:

1. Evolutionary computation component;
2. Feasibility filter;

3. Structural analysis, design, and optimization component (*SODA*);
4. Wind forces analyzer (wind load);
5. Evaluator; and
6. Visualization component.

The *evolutionary computation component* uses an evolutionary algorithm (EA) to produce the design concepts. This component is responsible for optimization of the configuration of a steel skeleton structure. The system allows the imposition of various requirements regarding the configuration of a given structural system. For example, the requirement of symmetry can be imposed or a requirement that a horizontal truss is placed on the top of a structural system. The function of the *feasibility filter* is to eliminate design concepts (filtering) not satisfying the imposed requirements. When an infeasible concept is generated, the feasibility filter discards it and the evolutionary computation component creates an additional design concept in its place. All feasible design concepts are then transferred to the *structural analysis, design, and optimization component*, which also receives input in the form of wind forces specific for a given design case produced by the *wind forces analyzer*. This component is a modified commercial system Wind Load V2.2.S, developed by Novel CyberSpace Tools. An additional feasibility check in terms of satisfying standard design criteria specified in the AISC-LRFD-93 design code is performed by *SODA* during the iterative process of local optimization of the steel skeleton structure. If a design concept turns out to be infeasible at this stage, it is assigned a very large weight value (which in turn corresponds to very low fitness, because it is a minimization problem), causing its almost zero probability of selection and survival.

Using the output from the evolutionary computation component, *SODA* produces a complete and detailed structural design. It also provides values of 25 design features, including the total weight, weight of bracings, weight of beams, weight of columns, number of bracings, etc. The value of the total weight of a structural system has been used to determine the fitness of each design. That has been done for the following three reasons. First, the total weight of a structural system is a traditional measure of its goodness or quality. Second, the total weight is at the same time a good estimator of the cost of a structural system and of its novelty (usually, novel design concepts are introduced to reduce the weight of a structure). Finally, the use of a utility-based fitness function would introduce bias and thus reduce the objectivity of the results. The writers are aware, however, that single-objective topological optimization might not be satisfactory in many cases and multiobjective optimization methods might provide better results. The fitness value, i.e., the total weight of a structural system, is transferred to the *population dynamics control* module in the evolutionary computation component. It is subsequently used by the EA selection mechanisms operating on population of design concepts. Finally, when this process is completed, its results are transferred to the *visualization component*.

Inventor 2001 does not analyze the generated concepts from the point of view of their constructability, although the feasibility filter could be expanded to accommodate constructability rules, if desired. This is done on purpose. Inventor 2001 generates many structural configurations that are stable and formally feasible but very complex and/or irregular and so would never be used for practical purposes. However, such impractical designs may gradually be evolved into much better designs considering their weight and constructability. Also, if necessary, the final products

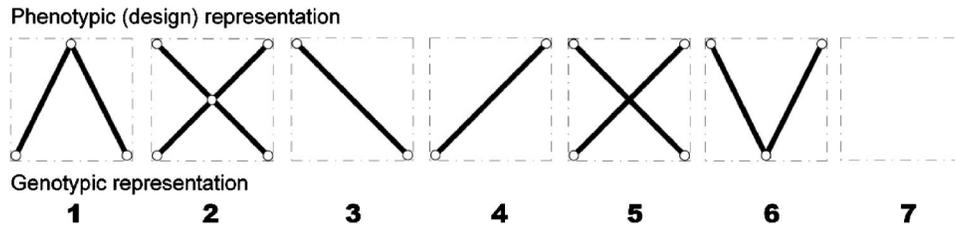


Fig. 1. Phenotypic and genotypic representation of bracing elements

of evolutionary design can always be improved by a human designer in terms of their constructability with a small weight penalty.

General Design Characteristics

Design Representation

In Inventor 2001, a structural system of a tall building is considered as a system of identical parallel planar transverse structures, which are the subject of design. In our case, it has been assumed that the buildings considered have three bays and that they are 16–36 stories tall. Bay widths were assumed to be 6.01, 7.32, or 7.92 m (20, 24, or 26 ft), and story heights could be 3.05, 3.66, or 4.27 m (10, 12, or 14 ft).

The representation space has been developed using the concept of division of the vertical structural grid of the building (the system of vertical and horizontal longitudinal lines of columns and beams, respectively) into units or cells. A cell can be described as a part of the vertical structural grid contained within the adjacent vertical and horizontal grid lines (Murawski et al. 2001). For each cell, six types of bracings (K, X, \ and /, simple X, and V) and two types of beams (rigid and hinged) are considered. Additionally, two types of ground connections (rigid and hinged) can be used for each connection of a column with its foundation. Using this approach, a given structural system can be represented as the sum of representations of its individual cells, each described by attributes identifying the existence and types of bracings and beams in a given cell, and by additional attributes describing column-foundation connections.

The subject of evolution is the placement and nature of such elements of structural systems as beams, bracings, and ground connections. These elements are described by multivalued attributes that are integer encoded as genotypes. A combination of attribute values defines a genotype of a single structural system. If a genotype contains only abstract (nominal) attribute values, then it represents a design concept. On the other hand, if it contains both abstract and numerical attribute values, then it defines a detailed design. A collection of all such combinations (genotypes) forms a genotypic space of the domain. The physical representa-

tion of a given attribute value is called its phenotype. For example, the value 2 of a gene representing a beam in the left bay at the level 6 has a phenotypic representation as a rigid beam in a steel skeleton structure at this specific location. A collection of all phenotypes corresponding to all combinations of attribute values (all genotypes) forms a phenotypic space of the domain. Thus, a clear distinction between genotypic and phenotypic spaces is made. The evolutionary search operates in the genotypic space, but fitness evaluation is performed in the phenotypic space. In this way, both abstract/qualitative and physical/numerical features of a given structural design are considered.

In this project, fixed-length genotypes are used as representations of various steel structural systems. The length of a genotype used in a given case depends on the number of cells in the structural system being considered, and that is obviously related to the number of stories. For each three-bay story, six genes (multivalued attributes) are used. Three of them describe bracings in the individual cells and are seven-value attributes (Fig. 1), while the remaining three describe beams in the individual cells and are three-value attributes (Fig. 2). For each structural system, four attributes describe column-foundation connections, and they are two-value attributes (Fig. 3). Thus, depending on the number of stories, the genotypes may contain from 100 genes (16 stories) to 220 genes (36 stories).

When the symmetry requirement is imposed, the feasible genotypes represent design concepts for symmetric structures only. In this case, the length of the genotype is the same as for an asymmetric structure with the same number of stories. However, constraints are imposed on the values of attributes describing corresponding cells on the individual levels and the centrally located cells (by this term, cells intersected by the Y axis of symmetry of the structural system are meant), if they occur in a given structural system. The attributes describing the centrally located cells can only assume values representing symmetrical bracings, for example, K-bracings, but not diagonal bracings. In the case of the outer cells (those that are not intersected by the Y axis of symmetry of the structural system), values of attributes describing corresponding structural members on the left and right of the Y axis of symmetry must obviously be identical, with the exception of diagonal bracings. In this case, a bracing /-type (Type 3) must

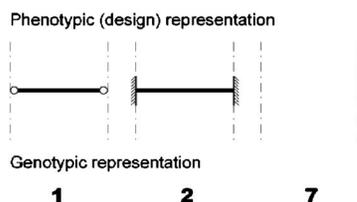


Fig. 2. Phenotypic and genotypic representation of beams

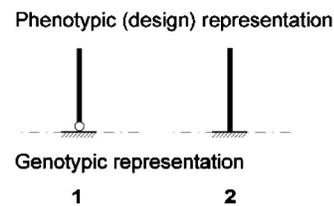


Fig. 3. Phenotypic and genotypic representation of ground connections

be accompanied by a corresponding bracing on the right of λ -type (Type 4). Symmetrical structural systems are generated in a two-step process. First, the representation of the centrally located and outer left cells is generated, and next the representation for the latter cells is replicated on the right side of the Y-axis of symmetry. When the evolutionary operators generate a design concept that is not symmetric, then a repair is made to force it to be symmetrical. A repair is understood here as a process in which a given genotype is modified so that it will represent a symmetric structure.

Evolutionary Algorithm Characteristics

Inventor 2001 uses an evolution strategy (ES) as its underlying evolutionary algorithm. Two versions of this algorithm were implemented, namely, $(\mu+\lambda)$ -ES and (μ,λ) -ES. In the former case, offspring designs compete with their parent designs for survival, whereas in the latter case offspring compete only with themselves. The parameter μ defines the number of parents in a population, and parameter λ defines the total number of offspring produced by parents at each generation. Evolution strategies have been selected as the evolutionary algorithm of choice because they work better with smaller population sizes. This is particularly important when an evaluation procedure is computationally expensive, as is the case with many engineering design problems. Also, when $\lambda > \mu$, then success rates of the stochastic operators, i.e., mutation and crossover, are improved. In other words, when the total number of offspring produced exceeds the number of parents, it is, on average, more likely that an offspring produced by a parent will be fitter than the parent (De Jong 2005).

As previously stated, there is a distinction between genotypic and phenotypic spaces. The evolutionary search operates only on the genotypic level. Genotypes are mapped into the phenotypic representation and evaluated. Truncation selection is the selection mechanism; only the fittest individuals in a population are chosen for reproduction. In the $(\mu+\lambda)$ -ES case, the surviving population is formed by selecting the fittest μ individuals from a combined population of parents and offspring of size $\mu+\lambda$. In the (μ,λ) -ES case, the population is formed using only an offspring population of size λ . Two major genetic operators have been used: mutation and parametrized uniform crossover (Spears and De Jong 1991). Also, it is possible in Inventor 2001 to randomly define mutation and crossover rates ("random" mutation and/or "random" crossover). While generating each offspring, the system randomly chooses values from zero to one from a uniform probability distribution for either, or both, the mutation or crossover rate. Thus, during the evolution process, mutation and crossover rates can be fixed throughout the whole process (fixed real values between 0 and 1), or they can change randomly whenever a new offspring is produced (random). Such an approach has several advantages: it allows more flexible exploration of the search space, it has a higher probability of escaping local optima when a randomly generated mutation rate of high value will be used at some point during the evolution, and it has a better chance of exploiting optimal regions in the search space when a randomly generated low mutation rate will cause only small variation of the offspring.

The overall fitness of a design is the total weight of the resulting steel structure. However, Inventor 2001 provides values of 25 characteristic features of a structural system that may also be used as evaluation criteria. A more detailed discussion of these attributes is provided subsequently.

Another important parameter describing the evolutionary design process is the length of the evolutionary run. It is usually

Table 1. Load Magnitudes Used in Reported Experiments

Load parameter	Value(s)
Dead load magnitude	2.39 kN/m ² (50 psf)
Live load magnitude	
Building	4.78 kN/m ² (100 psf)
Roof	1.43 kN/m ² (30 psf)
Wind load	
Wind speed	44.69 m/s(100 mi/h)
Wind importance factor	1.0
Wind exposure category	C

defined either by the number of generations produced during the evolutionary process, or by the total number of fitness evaluations performed. In this paper the length of a run was controlled by the number of generations produced. As the result of numerous design experiments, the writers have realized that there are significant qualitative differences when comparing results of short- and long-term evolutionary design processes. By a short-term evolutionary design process, the writers mean a process involving less than 1,000 generations, while long-term processes have more than 1,000 generations.

Design of Experiments

Experimental Parameters

The objective of the experiments reported in the paper was to determine the feasibility of evolutionary computation in steel structural design. It has been accomplished through analysis of the results of a number of experiments. In the experiments performed, the following classes of structural system designs in tall buildings have been considered:

- Number of bays: 3,
- Structure height: 26, 32, or 36 stories,
- Bay width: 6.01 m (20 ft),
- Story height: 4.27 m (14 ft),
- Distance between transverse systems: 6.01 m (20 ft),
- Requirements: no specific requirements imposed or symmetry requirement, and
- Analysis method: first-order.

In the experiments, complete structural designs were produced under realistic assumptions. However, several simplifications were made to reduce the computational complexity and cost while preserving the fundamental soundness of the results. In the analysis, three combinations of loads were considered, including:

- Dead+live,
- Dead+wind, and
- Dead+0.75(live+wind).

Only one wind direction was considered, and that might reduce the natural tendency of structures to evolve toward symmetry. The magnitudes of dead, live, and wind loads used in the design experiments are given in Table 1.

In an exhaustive parameter search performed for short-term evolution, 36-story building designs were used, whereas for the long-term experiments, 26-story, 32-story, and 36-story buildings were considered.

In most of the evolutionary computation applications, the initial population of parents is usually generated randomly (Bäck et al. 1997); however, in this project a different approach has been used. Twelve feasible designs have been preselected to

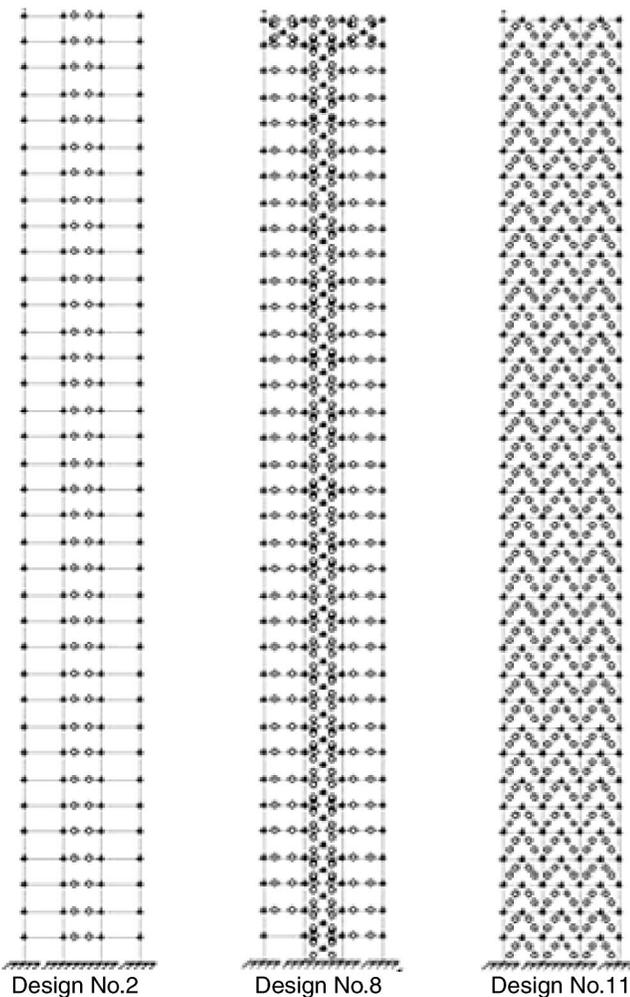


Fig. 4. Examples of designs used as initial parents in experiments

form a pool of initial parents for the evolutionary processes. The initial group of 12 parents consisted of designs that were considered appropriate (called “suboptimal” here) for a given design situation, as well as designs that could be characterized as rather inappropriate (called “poor” here) (see Fig. 4). The individual designs within the group can be described as:

- Design No. 1—one-bay centrally located rigid frame,
- Design No. 2—two one-bay rigid frames located in outer bays,
- Design No. 3—three-bay rigid frame,
- Design No. 4—one-bay centrally located rigid frame with one horizontal truss,
- Design No. 5—one-bay centrally located rigid frame with centrally located vertical truss,
- Design No. 6—two one-bay rigid frames located in outer bays with two vertical trusses located in outer bays,
- Design No. 7—three-bay rigid frame with three vertical trusses,
- Design No. 8—one-bay centrally located rigid frame with one horizontal truss and centrally located vertical truss,
- Design No. 9—one-bay centrally located vertical truss,
- Design No. 10—two one-bay vertical trusses located in outer bays,
- Design No. 11—three one-bay vertical trusses, and
- Design No. 12—three-bay rigid frame with one horizontal truss.

Next, the group was arbitrarily divided into four populations, each of three parents, and each one was evolved independently. Population No. 1 consisted of Design Nos. 1, 5, and 9. Population No. 2 included Design Nos. 2, 6, and 10. Finally, Population No. 3 contained Design Nos. 3, 7, and 11, and Population No. 4 included Design Nos. 4, 8, and 12. For the long-term experiments, designs from Population No. 1 and Population No. 4 have been used as initial parents. Experiments with one large population of all 12 designs have been also conducted. Several examples of initial parents used in the experiments are shown in Fig. 4.

The genotypes of 26-story, 32-story, and 36-story design concepts consisted of 160, 196, and 220 genes, respectively. Thus, for example, 220 gene-long chromosomes had 108 genes that had seven values (bracing elements), 108 genes with three values (beam elements), and four that had two values (ground connections). In the experiments, the following EA parameters were used:

- Population size: $\mu=3$, $\mu=9$, or $\mu=12$, and $\lambda = \mu \cdot 5$;
- Mutation rates: random, 0.10, 0.20, 0.30, 0.50, 0.86, 0.90;
- Crossover rates: random, 0.10, 0.20, 0.30, 0.50, 0.54; and
- Number of generations: 100, 1,000, 2,500, 5,000, 10,000.

Research Questions and Conducted Experiments

In the study, answers to the following questions were sought:

1. What can be learned about evolutionary design as a useful paradigm for generating novel and creative designs for structural engineering purposes?
2. Which evolutionary computation parameters and their rates are most suitable for the evolution of structural systems of tall building designs?

To answer these two questions, the reported experiments, involving every possible combination of mutation and crossover rates from the set of predefined values, were performed. The predefined values for mutation rates were limited to: none, random, 0.10, 0.20, 0.30, 0.50, and 0.90. The corresponding set of predefined values for the crossover operator included: none, random, 0.10, 0.20, 0.30, 0.50. Several (five or more) experiments were run with different random seed values for each possible combination of parameters and for each of the four population building designs (as described previously). An exhaustive search has been conducted looking for novel designs produced by the system, the most suitable operators, and their rates for evolutionary design processes.

3. What is the impact of population size, and hence population diversity, for the evolution of structural systems of tall buildings?

In order to answer this question, the following experiments were designed. First, several experiments with one population of all original 12 parents for different parameter values were run. Then, the results obtained from these runs were compared with results from the previous experiments, which used four populations of three parents and exactly the same EA parameters.

4. Can the symmetry requirement improve the evolution of structural systems of tall building designs? Can better results be achieved using the symmetry requirement?

Estimation of symmetry importance was done in the following way. Experiments with the same four populations of three parents were run with all the parameters constant as in the previous experiments except for imposing the symmetry

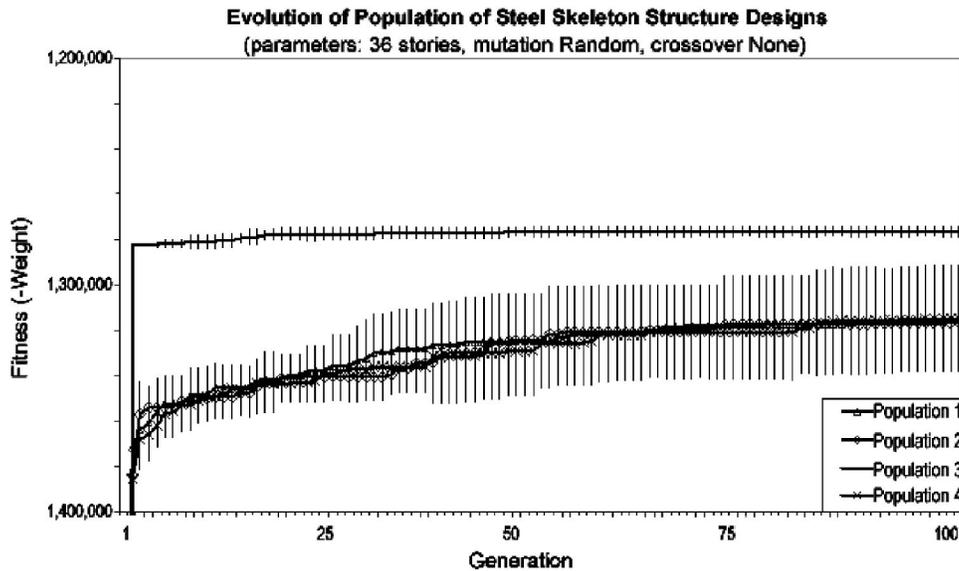


Fig. 5. Evolution of four populations of steel skeleton structure designs

requirement. Then, the corresponding results for each of the four populations were compared.

5. What is a qualitative and quantitative difference between long-term evolutionary processes and short-term processes?

To answer this question, “average” populations (Population Nos. 1 and 4) and “optimal” and “poor” evolutionary parameters were chosen based on the results obtained from short-term experiments. Thus, Population No. 4 with mutation rate “random” and no crossover (previously determined as being the “optimal” parameters’ rates) was chosen and evolved for 2,500 generations. In the second experiment, Population No. 1 and very high rates of both mutation and crossover (“poor” parameters’ rates) were used and the process run for 10,000 generations. Next, fitness values after long-term processes with results produced after 100 generations were compared.

6. Can any emerging structural shaping/topological patterns be identified in the evolutionary process? What is the engineering significance of these patterns? Do these patterns occur also in long-term evolutionary processes, and, if so, what are the differences?

To get some insight into emerging patterns occurring during the evolution processes, the fitness function, the previously described 25 characteristic features of the steel structural system, and the topology of generated design concepts were analyzed. The emergence of interesting patterns was observed on all three levels.

Experimental Results

In this section, the results of the conducted experiments are presented and arranged as observations, following the outline of questions posed in the previous section.

Novel and Creative Designs

In addition to testing the outcomes for various combinations of parameters throughout the experiments, a search for novel and creative designs of steel structural systems in tall buildings was

conducted. This search considered not only fitness, represented by overall weight of the structure, but also interesting and innovative substructures. The initial set of 12 parents included a design (Design No. 11) that is regarded as appropriate (and called “suboptimal” by the writers) for the class of 36-story buildings (see Fig. 4). In fact, its overall fitness was very good ($581,874.5 \text{ kg} = 1,282,813.6 \text{ lb}$), and it was the best fitness value (in this case, the lowest value because it is a weight minimization problem) among all the designs that were chosen as initial parents. During the experiments, a search for novel designs was conducted that might be better in terms of their fitness values than this already well-known design. Interestingly, evolutionary processes were able to find designs of 36-story buildings that were better than this well-known design. Fig. 5 shows typical evolutionary progress for the four populations. It presents mean best fitness values (thick lines) at each of 100 generations, and their corresponding 95% confidence intervals (thin vertical lines). In the experiments shown on the graph, a random rate of mutation was used with no crossover. The symmetry requirement was not imposed. As can be easily noticed in Fig. 5, the best Population, No. 3, containing the very fit Design No. 11, improves very slowly—in fact, almost nothing in terms of its mean total weight. On the other hand, the remaining populations, containing rather poor designs, were able to evolve substantially better designs compared to their initial parents, but nevertheless they were not able to produce better designs than Population No. 3 within 100 generations. It is also worth mentioning that there is a large qualitative difference between Population No. 3 and the remaining populations. When the population contains a very fit design, it quickly produces very similar, and hence very fit, children that replace other designs in the pool. The population quickly becomes almost homogenous, causing the fitness variance within the population to be very small. This phenomenon can also be easily noticed by observing the lengths of 95% confidence intervals (thin vertical lines) in Fig. 5. On the other hand, populations with relatively poor designs can be characterized by large fitness variance, and thus larger diversity within the population.

The best designs of steel skeleton structures were obtained when the symmetry requirement was imposed. Detailed analysis of the importance of symmetry in the reported study is presented

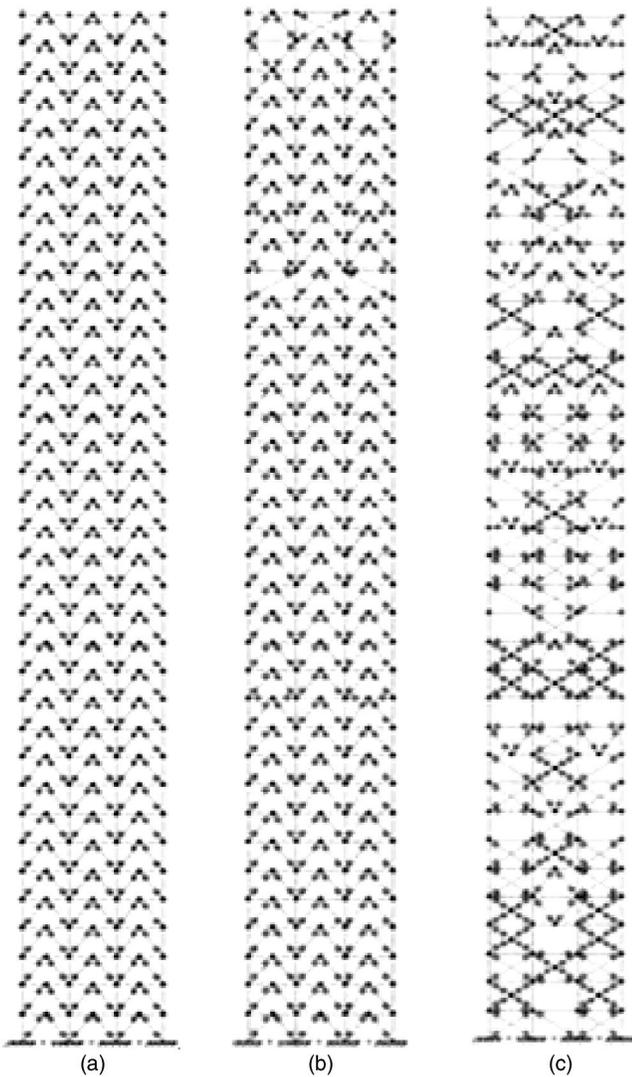


Fig. 6. (a) Already well-known (sub-) optimal design; (b) best design produced by Population 3; (c) best design produced by Population 4

in a subsequent section. In this section the topologies of the best designs are shown that were obtained in short-term experiments. Fig. 6 shows three fit designs of steel structural systems of 36-story buildings. Fig. 6(a) presents Design No. 11, a fit parent from Population No. 3. Its fitness (weight) was equal to 581,874 kg (1,282,814 lb). The design shown in Fig. 6(b) represents the best design obtained in all short-term experiments. It was generated during the evolution of Population No. 3. Its fitness was

equal to 577,540 kg (1,273,257 lb), which gives 0.75% improvement as compared to the initial parent. Although this does not seem to be a big improvement, we have to realize that in this case the savings represent more than 4,309 kg (9,500 lb) of structural steel. Fig. 6(c) shows the best design generated by the evolution of Population No. 4. Its fitness was equal to 578,007 kg (1,274,287 lb). This corresponds to improvement in fitness by 187% compared to the best initial parent from Population No. 4 (1,663,786 kg=3,668,021 lb), and a 0.67% improvement compared to Design No. 11 from Population No. 3. Thus, starting with poorer designs causes substantial evolutionary progress but it does not necessarily produce best designs in the short term. On the other hand, it is clearly visible that the best design presented in Fig. 6(b) is very similar to its initial parent shown in Fig. 6(a). This again confirms the writers' previous hypothesis that, when the evolution starts with a population containing a fit design, the variance within the population is small and all generated designs are similar to the initial parent. Fig. 6(c) presents a good design also, but in this case its topology is dramatically different from all already known designs. It can be also observed that there are some very interesting emergent one-, two-, and multistory sub-structures created by the evolution. They are described in detail in a subsequent section.

As the writers saw in many experiments, when the aim is to look for innovative designs, it is better to start with poorer designs, i.e., to start in the "valley" of the fitness landscape. When one starts close to a landscape peak, one might not be able to overcome this peak and find other peaks in the landscape that might offer even better fitness values and innovative design concepts.

Effects of Evolutionary Computation Parameters and Rates

Both the mutation and crossover operators have been examined, adjusting their combinations and their rates, and trying to achieve optimal progress of the evolution process and to avoid stagnation. Sample experimental results for Population No. 1 are presented in Table 2. The combinations of parameter rates that produced the best results are marked with boldface type.

As can be observed in Table 2, the best results were achieved using random mutation operator with various values of crossover operator. For example, for Population No. 1 the best solution was obtained using a random mutation operator and 0.50 crossover rate. The set of parameter rates that provided the best results has been called "optimal" for evolving steel skeleton structure designs. On the other hand, the set of parameter rates that generated relatively worse designs was named "poor." In the latter set, very high values of both mutation and crossover rates were included.

Table 2. Mean Best Fitness Values after 100 Generations for Different Parameter Combinations for Population 1

Mutation	Crossover					
	None	Random	0.10	0.20	0.30	0.50
None	X	3,543,720	3,543,720	3,543,720	3,543,720	3,543,720
Random	1,314,886	1,315,537	1,317,779	1,311,848	1,303,392	1,289,953
0.10	1,339,799	1,317,366	1,311,364	1,337,335	1,313,611	1,305,869
0.20	1,343,238	1,333,473	1,332,559	1,328,408	1,332,081	1,309,788
0.30	1,325,117	1,314,282	1,343,465	1,322,571	1,319,159	1,333,488
0.50	1,320,132	1,343,238	1,334,990	1,330,793	1,339,440	1,343,080
0.90	1,348,577	1,334,623	1,312,020	1,337,560	1,332,220	1,335,350

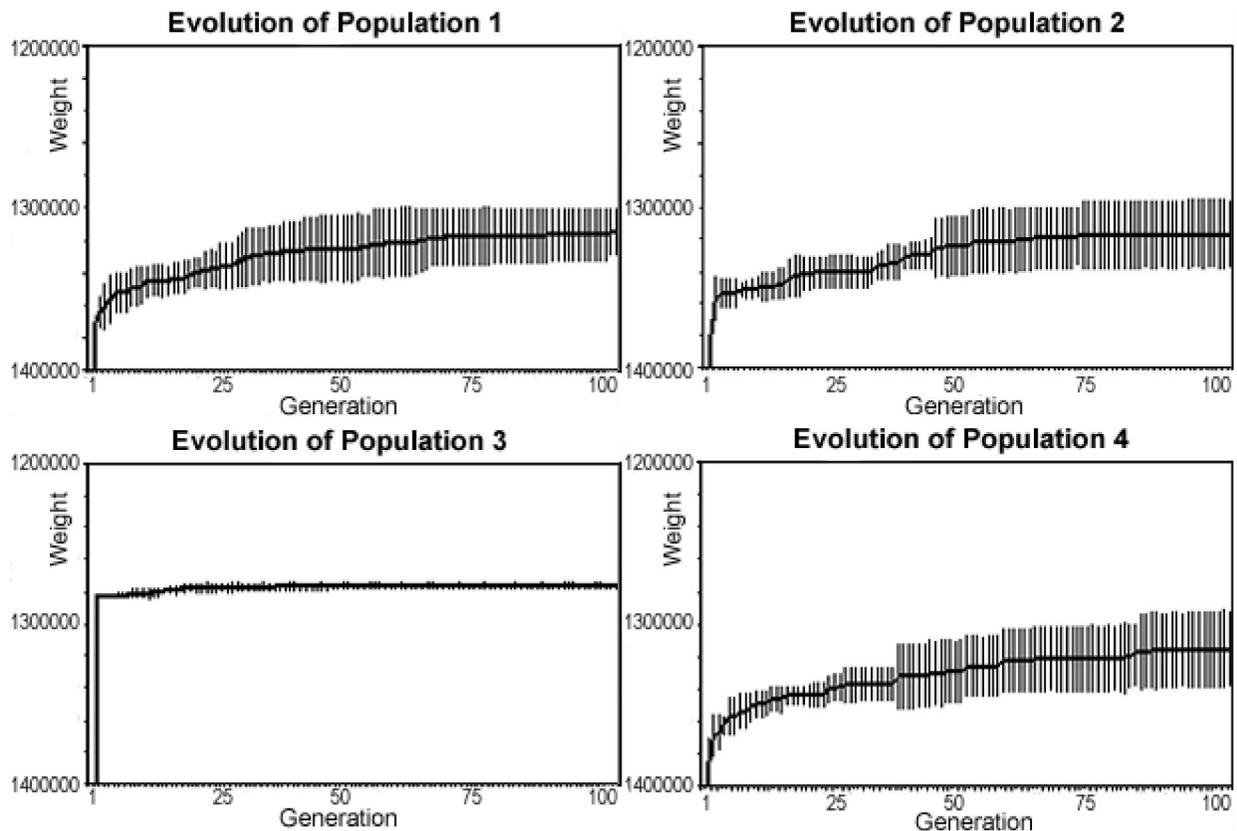


Fig. 7. Evolution of four populations using “optimal” parameter rates of crossover and mutation

Fig. 7 presents typical results from experiments using a set of “optimal” parameters for the individual populations as described previously. As one can easily notice in this figure, the evolutionary processes using the “optimal” parameters not only achieved best results but also progressed rapidly during the entire run.

On the other hand, the worst results were obtained during experiments in which the only working operator was crossover. In this case, all individuals in the population converged rapidly (after 3–4 generations) to one of the initial parents, and the population became homogeneous. When all designs in the population became identical, then further progress of evolution using only the crossover operator was impossible. At that point, crossover alone could not bring in any new information to the evolving population, and that caused premature convergence very quickly in the evolutionary process.

As the experiments have shown, conclusions drawn for Population No. 1 are also valid for Population Nos. 2 and 4. However, in the case of Population No. 3 the situation was dramatically different. Almost no significant progress in terms of better fitness for this population could be achieved. Because of the very fit design (Design No. 11), the entire population converged to this design, or its very slight mutation, and was unable to produce a better solution no matter what parameters, or their combinations, were used. The process very quickly stagnated, and the population became homogeneous.

As the writers were able to observe during the conducted experiments, a very good evolution progress could be obtained starting from rather poor parents. Starting with very fit parents caused the population to be trapped in a landscape peak, or a basin of attraction, and evolution could not produce substantially better solutions. As these results were analyzed, the small population

size (only three parents) was suspected to be the reason that almost no significant progress could be made for the population containing a very fit parent. Thus, further experiments were conducted with larger population sizes. Results of these investigations are presented in the next section.

Effects of Population Size and Diversity

The question that naturally occurred during the conducted study was whether it is possible to combine the very good evolutionary progress observed in the case of Population Nos. 1, 2, and 4 with the very fit parents of Population No. 3, and finally achieve the best solutions. Therefore, all four initial populations were combined into one relatively large population of 12 parents. Each parent produced five children, as in previous experiments. For experiments with one large population, the most promising evolutionary parameters (random mutation, no crossover, symmetry constraint) were used. Indeed, the larger population size allowed the writers to achieve better results. Fig. 8 shows the mean best fitness values for 12 parents compared to the values obtained for Population Nos. 3 and 4. As Fig. 8 clearly shows, the variance (diversity) has increased compared to the results obtained during the evolution of Population No. 3 alone. On the other hand, it is still smaller than the corresponding results for Population No. 4. Nevertheless, this slightly increased variance allows the large population of 12 parents to achieve a better mean fitness than the highest one achieved so far by evolving Population No. 3 (proving this statistically would require more experiments because, as is visible in Fig. 8, the 95% confidence intervals of Population No. 3 and the large population of 12 parents slightly overlap). The mean best fitness of the large population after 100 generations

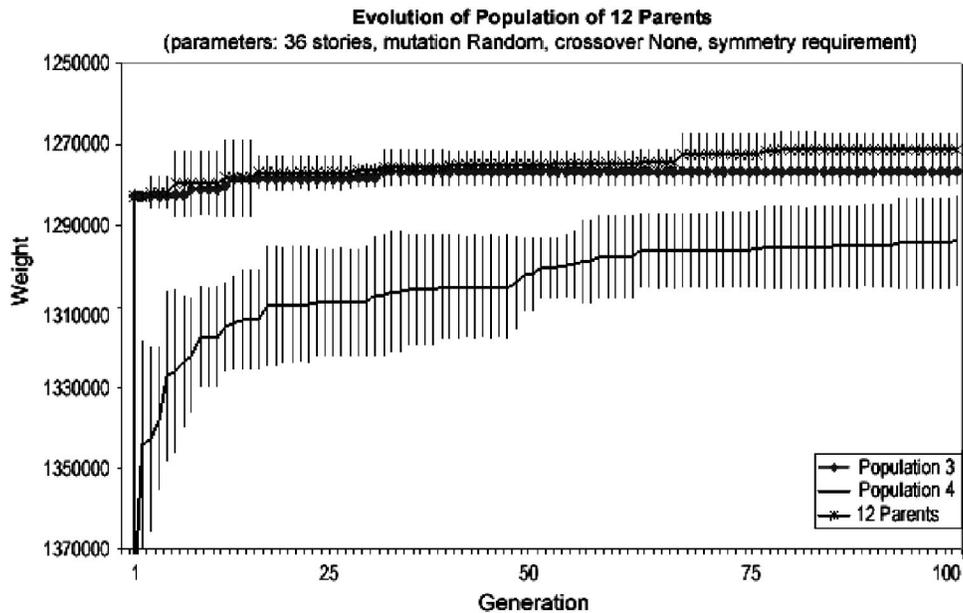


Fig. 8. Evolution of combined population versus individual Populations 3 and 4

was equal to 576,630 kg (1,271,251 lb), whereas the corresponding mean best fitness of Population No. 3 was equal to 579,174 kg (1,276,859 lb). That constitutes a 0.44% average fitness improvement. The best design produced by the large population had a fitness equal to 576,026 kg (1,269,921 lb), and this is more than 1.0% better fitness compared to the best initial parent in the large population (Design No. 11).

Thus, as our experiments have shown, it is recommended to use larger population sizes in evolutionary design of steel structural systems in tall buildings. This can be justified by the increased diversity of the population of designs and better progress of the evolutionary processes. On the other hand, there is always a trade-off between using large and small population sizes in evolutionary design. Large populations require many more fitness evaluations than smaller ones. Thus, when a fitness evaluation of a design concept is computationally expensive, as is usually the case, one has to choose whether to use large populations and shorter runs, or smaller populations and substantially longer runs.

Effects of Symmetry Requirement

Symmetry of structures is a very important property from the structural engineering point of view. Almost all steel structural systems are symmetric, and that is considered highly desirable for various reasons (aesthetics, constructability, structural behavior, etc.). The writers wanted to investigate whether the evolutionary process can also justify this trend. The symmetry requirement was imposed on all four initial populations of parents and their offspring. In these experiments, “optimal” evolutionary parameters were used: random rate of mutation and no crossover. Next, these results were compared with previous results obtained for the same populations and parameters but evolved without the symmetry requirement. Results are presented in Figs. 9 and 10.

Fig. 9 presents results obtained for Population No. 4, and similar patterns were also obtained for Population Nos. 1 and 2. Generally the symmetry requirement has a positive impact on the evolutionary processes. Although the results obtained are not statistically significant because the 95% confidence intervals overlap, it can be easily observed that, in general, evolutionary pro-

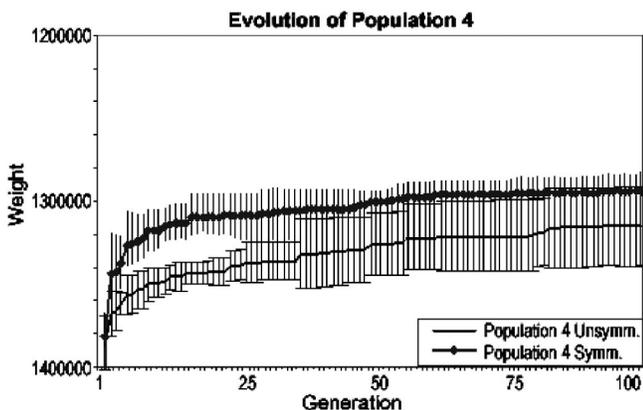


Fig. 9. Effects of symmetry requirement (Population 4)

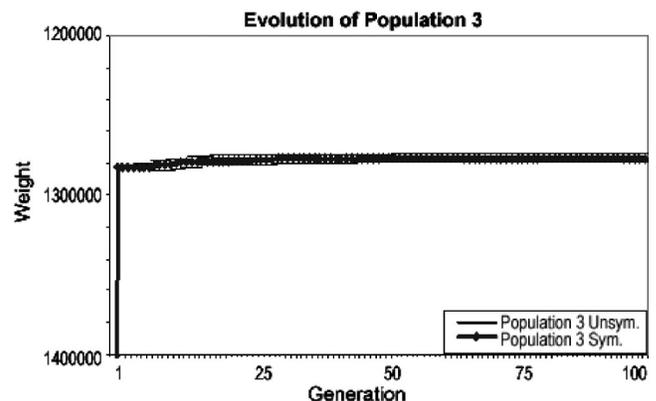


Fig. 10. Effects of symmetry requirement (Population 3)

Table 3. Improvements in Mean Best Fitness of Designs due to Symmetry Requirement

Population	Asymmetric	Symmetric	Fitness improvement (lbs)	Fitness improvement (%)
Population 1	1,314,886	1,297,609	17,277	1.33
Population 2	1,316,842	1,293,572	23,270	1.80
Population 3	1,276,382	1,276,859	-477	-0.04
Population 4	1,314,967	1,293,769	21,198	1.64

cesses with a symmetry requirement are superior to the corresponding processes evolved without this requirement.

To give some quantitative measure of improvement, results of the mean best fitness after 100 generations for each of the four populations were compared, and results are presented in Table 3. As this table shows, the symmetry requirement can improve designs' fitness about 1.5% on average. Population No. 3 is the only exception, as is shown in Fig. 10. Imposing the symmetry requirement does not improve the quality of the evolved designs. In fact, even the opposite relation can be observed as compared to the other populations. The symmetry constraint causes a very small reduction of the best design fitness for Population No. 3. The writers' explanation of this fact is that the initial parent in Population No. 3 with a very good fitness value already has a highly regular and symmetric structure. Symmetrical changes in the design topology introduce larger disruption of this regular pattern. On the other hand, nonsymmetrical changes are less disruptive, and can bring some slight fitness gain, especially when they occur in the places where internal forces are not as large and bracing of type K can be replaced with other types of bracings [see also Fig. 6(b)].

Qualitative and Quantitative Differences between Long- and Short-Term Evolutionary Design

The subject of these experiments was to compare the values obtained after 100 generations (short-term experiments) with the final values obtained in the long-term evolution. Changes in the fitness function as well as other evaluation criteria have been analyzed.

A series of experiments with Population Nos. 3 and 4 has been performed first, with each evolved for 1,000 generations. The experiments were conducted with random mutation, no crossover, and the symmetry requirement. The subjects of interest were

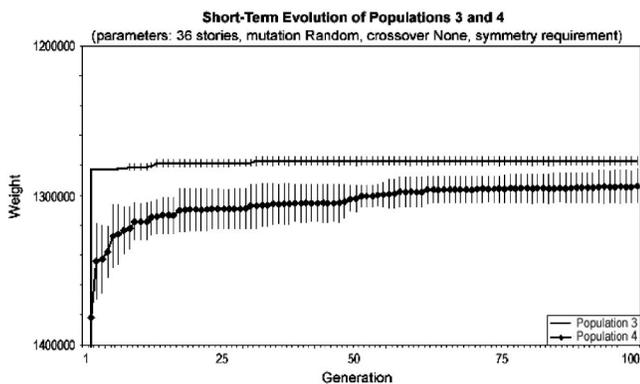


Fig. 11. Short-term evolution of Populations 3 and 4 (100 generations)

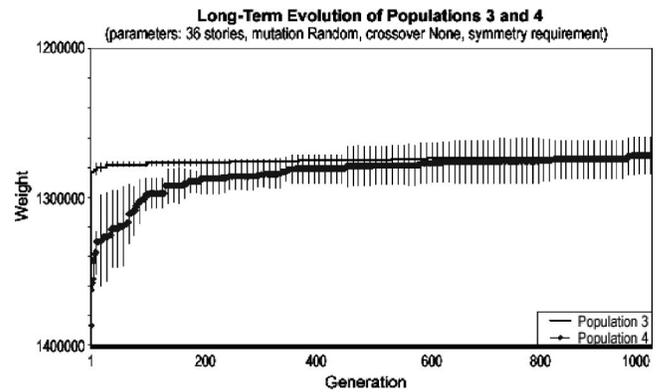


Fig. 12. Long-term evolution of Populations 3 and 4 (1,000 generations)

whether the rapid evolutionary progress of Population No. 4 compared to the rather poor progress of Population No. 3 shown in short-term experiments with 100 generations (see Fig. 11) can be extended to a larger number of generations, and if there is some point where population No. 4 is better than Population No. 3 in terms of the mean best fitness.

As is shown in Fig. 12, Population No. 4 indeed extends its rapid evolutionary growth to a large number of generations. Population No. 3 improves only slightly over the entire long-term evolutionary run. In fact, at about the 950th generation, mean best

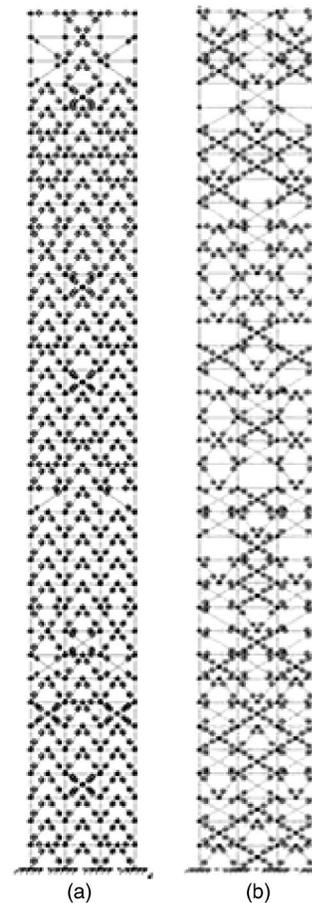


Fig. 13. Best designs produced during long-term experiments by (a) Population 3; and (b) Population 4

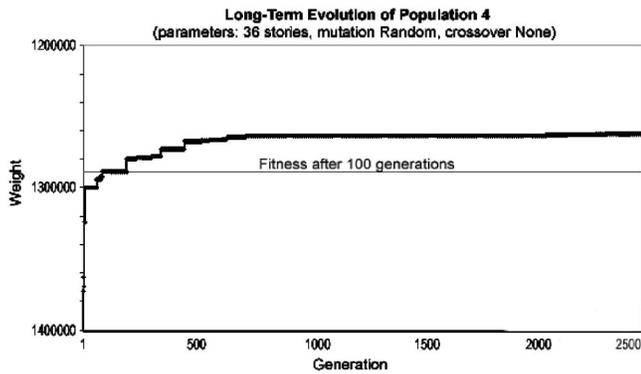


Fig. 14. Best fitness values for Population 4 evolved for 2,500 generations

fitness of the best design in Population No. 4 was better than the corresponding value for Population No. 3. The final mean best fitness after 1,000 generations was equal to 576,939 kg (1,271,932 lb) and 577,459 kg (1,273,078 lb) for Population Nos. 4 and 3, respectively. The fitness improvement between the 100th and 1,000th generation was equal to 1.72% for Population No. 4, compared to 0.30% obtained for Population No. 3.

The best design produced by Population No. 4 in the long-term experiments had fitness equal to 573,148 kg (1,263,574 lb). The corresponding best design produced by Population No. 3 had a fitness of 574,801 kg (1,267,220 lb). Both designs are presented in Fig. 13.

In another long-term experiment, 36-story buildings have been evolved for 2,500 generations. The final best fitness value was equal to 572,434 kg (1,262,001 lb), whereas after 100 generations this value was equal to 584,438 kg (1,288,465 lb). This represents a 2.05% improvement in the fitness of the design. The progress of evolutionary processes in this experiment is presented in Fig. 14. In this experiment “optimal” rates of mutation and crossover were used, and the chart shows that evolution progressed rapidly for a large number of generations. Even after 2,000 generations, there was still some progress being made.

In yet another long-term experiment, 32-story buildings and “poor” rates of mutation and crossover parameters have been used, namely, a mutation rate set to 0.86 and a crossover rate set to 0.54. In this experiment, Population No. 1 has been evolved for 10,000 generations. The progress of evolutionary processes for Population No. 1 is presented in Fig. 15. The fitness of the best

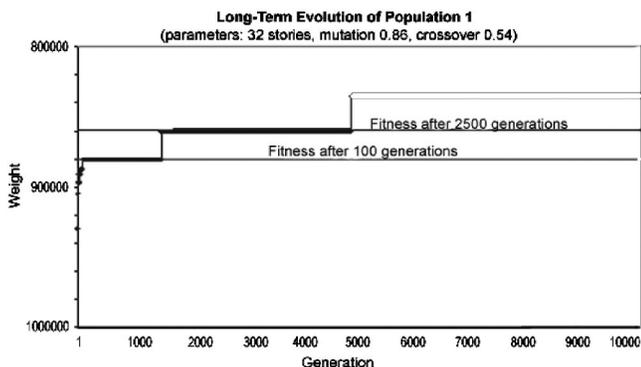


Fig. 15. Best fitness values for Population 1 evolved for 10,000 generations

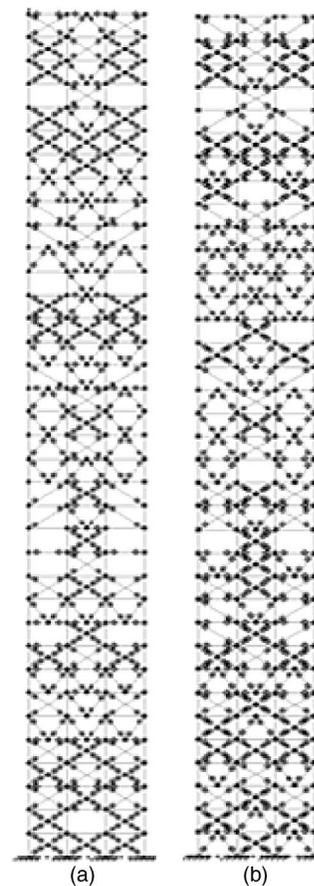


Fig. 16. (a) Fittest design after 100 generations; and (b) fittest design after 2,500 generations

design after 10,000 generations was equal to 378,678 kg (834,843 lb), and after 100 generations, 399,204 kg (880,094 lb). This gives an improvement in the fitness value equal to 5.42%.

Although a relatively small number of long-term experiments have been conducted using distinct sets of parameter values, some qualitative differences are immediately visible. As can be observed in Figs. 14 and 15, the initial evolutionary parameter settings have a tremendous influence on the behavior of the evolutionary processes. For example, for the experiment using the “optimal” parameter values shown in Fig. 14, one can see that evolution progresses rapidly and continuously. On the other hand, in the experiment shown in Fig. 15, where very high rates of mutation and crossover operators have been used, occasional sudden jumps in the fitness function value can be observed with no progress in between. Hence, lower values of mutation and crossover rates seem to be more favorable for sustaining good evolutionary progress, at least in this particular domain. They steadily guide the evolution toward better solutions. On the other hand, high values are more disruptive and often resemble a kind of random search in the design space (Kicinger et al. 2002).

A qualitative comparison of the best designs produced by the last two described evolutionary processes was also performed. Fig. 16 presents the best designs obtained from the experiment with 2,500 generations. Here again, some interesting emerging patterns can be identified, which are described in detail hereafter.

Differences between the fittest designs in the two long-term experiments with respect to the other 25 evaluation criteria have been also investigated. Results are presented in Figs. 17–20.

Comparison of Structural Elements (Quantity)

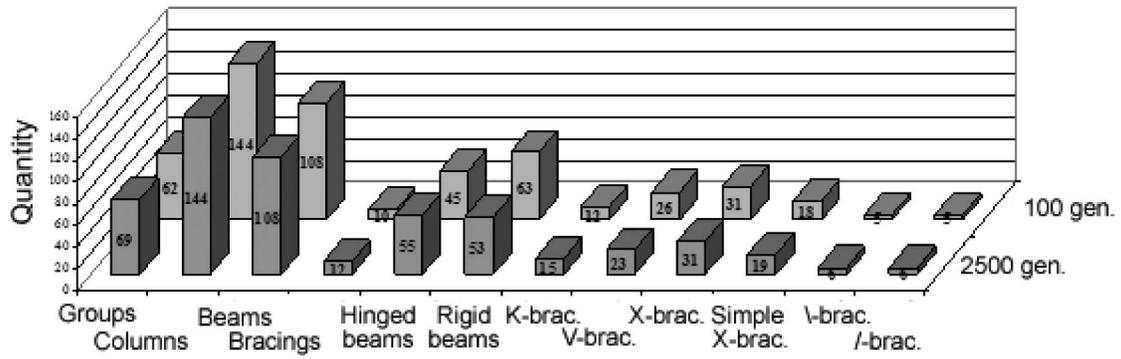


Fig. 17. Quantities of appropriate structural elements in fittest designs

Comparison of Structural Elements (Weight)

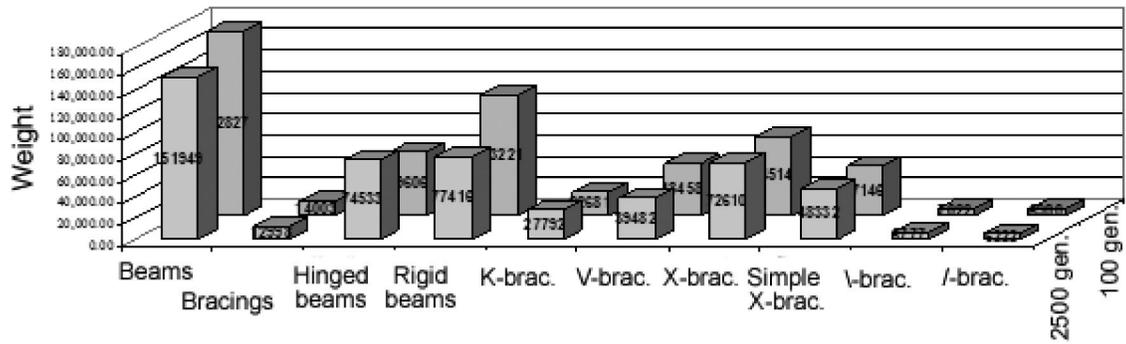


Fig. 18. Weights of appropriate structural elements in fittest designs

Comparison of Structural Elements (Quantity)

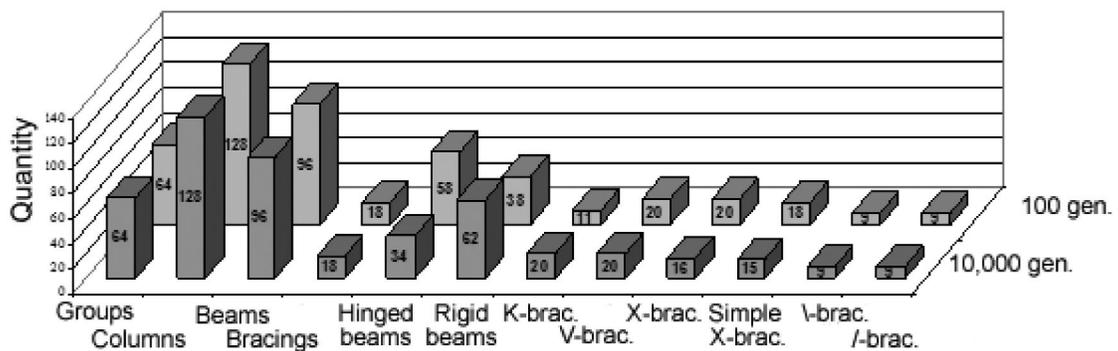


Fig. 19. Quantities of appropriate structural elements in fittest designs

Comparison of Structural Elements (Weight)

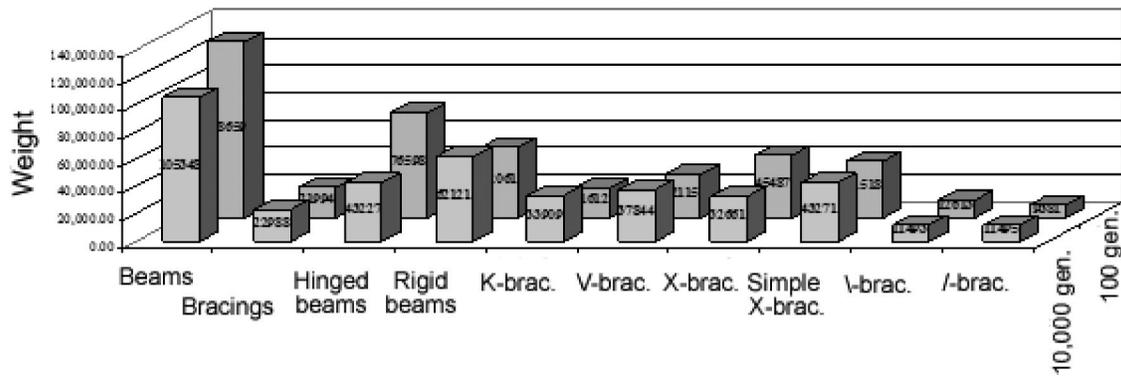


Fig. 20. Weights of appropriate structural elements in fittest designs

Figs. 17 and 18 show the changes in values of 25 evaluation criteria for the experiment with Population No. 4 evolved for 2,500 generations. It can be observed in both figures that the major differences between the two best designs produced after 100 and 2,500 generations appear in the number of hinged and rigid beams and K and V bracings. In the first case, hinged beams replace some rigid beams, and K bracings replace some V brac-

Table 4. Comparison of the Cross Sections of All Structural Members of the Best Design Obtained in the Long-Term Experiments (after 2,500 Generations) and the Suboptimal Design No. 11 from Population No. 3

Members	Design No. 11 in Population No. 3	Best design after 2,500 generations
Column 1	W 36 × 848	W 36 × 848
Columns 1–5	W 36 × 848	W 36 × 848
Columns 5–9	W 36 × 848	W 36 × 848
Columns 9–13	W 36 × 798	W 36 × 798
Columns 13–17	W 44 × 335	W 40 × 431
Columns 17–21	W 44 × 335	W 40 × 431
Columns 21–25	W 40 × 167	W 40 × 149
Columns 25–29	W 30 × 108	W 30 × 116
Columns 29–33	W 30 × 108	W 30 × 116
Columns 33–36	W 30 × 108	W 24 × 68
Beams 1–5	W 30 × 108	W 24 × 68
Beams 5–9	W 30 × 108	W 24 × 68
Beams 9–13	W 30 × 108	W 24 × 68
Beams 13–17	W 30 × 108	W 24 × 68, 30 × 116
Beams 17–21	W 30 × 108	W 14 × 48, 24 × 68
Beams 21–25	W 30 × 108	W 24 × 68
Beams 25–29	W 30 × 108	W 24 × 68
Beams 29–33	W 30 × 108	W 24 × 68
Beams 33–36	W 30 × 108	W 24 × 68
Bracings 1-5	W 12 × 53	W 10 × 54, 18 × 55
Bracings 5-9	W 18 × 50	W 10 × 54
Bracings 9-13	W 18 × 50	W 10 × 54, 12 × 58
Bracings 13-17	W 18 × 50	W 10 × 54
Bracings 17-21	W 18 × 50	W 10 × 54
Bracings 21-25	W 12 × 53	W 10 × 54
Bracings 25-29	W 18 × 50	W 10 × 54, 8 × 31
Bracings 29-33	W 18 × 50	W 16 × 31, 10 × 54, 8 × 31
Bracings 33-36	W 18 × 50	W 16 × 31, 8 × 31

ings. Also, a comparison of the cross sections of all structural members of the best design produced after 2,500 generations with the optimal Design No. 11 from Population No. 3 has been conducted. The types of cross sections calculated by SODA for both designs are presented in Table 4.

The analysis of changes in the 25 evaluation criteria for the long-term experiment conducted for 10,000 generations revealed that the major differences between two fittest designs after 100 and 10,000 generations were in the ratio of hinged/rigid beams and in the number of K, V, and X bracings. The final design had more rigid beams, less hinged beams, more K and V bracings, and less X bracings compared to the design after 100 generations. These results are presented in Figs. 19 and 20.

The observed changes can be described in terms of structural shaping as a tendency to design structures in the form of braced rigid frames (increased number of rigid connections between columns and beams) with K or V bracings, instead of X bracings. The changes are consistent with our understanding of steel structural systems of tall buildings.

Emergence

As the conducted experiments have shown, evolutionary processes produced gradually more and more fit designs. The writers were interested in identifying emerging structural shaping patterns during the evolution process, which had a positive impact on

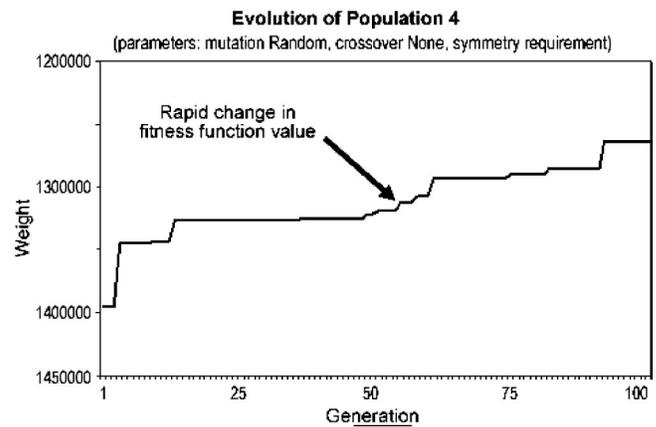


Fig. 21. Evolution of Population 4 with rapid changes in fitness function

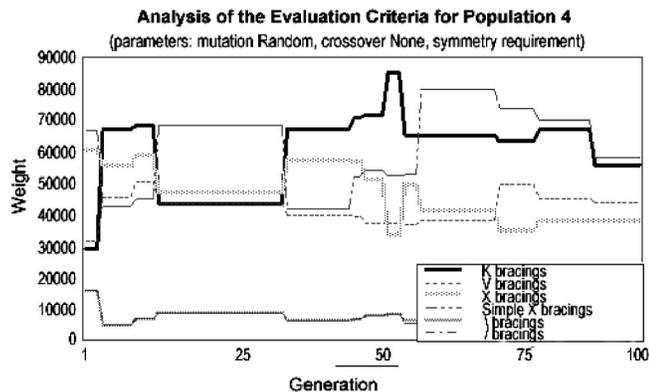


Fig. 22. Analysis of evaluation criteria for evolution of Population 4

the quality of generated designs. This knowledge might help us better understand nonlinear interactions taking place among various parts of evolving steel skeleton structures, and also to identify the most critical elements of the system. First, the 25 characteristic features of evolved designs (bracings, beams, and columns) in short-term experiments were compared and analyzed in a search for interesting emerging patterns. Emergent behavior was observed in several instances. Usually interesting patterns occurred during rapid changes in the value of the fitness function, as shown in Fig. 21. Changes in the values of the 25 evaluation criteria at such interesting points were thoroughly investigated during the evolution process. In particular, in the evolutionary process presented in Fig. 22, the following pattern occurred. Weight (and also number) of X bracings rapidly decreased, and weight of K bracings rapidly increased. Thus, significant improvements were possible by replacing X bracings with K bracing in the evolved design, as it is known in structural engineering. Similar patterns found during the long-term experiments were described previously. In fact, it is well known that K bracings are much better than X bracings in steel skeleton structures, considering their weight and provided rigidity.

Another important emerging behavior that was observed was the forming of substructures, or “building blocks.” One of the characteristics of this design representation space is that, although the dimensionality is huge, there may not be a great deal of variability from story to story in the tall building. Once a very fit “floor” has been found, they seem to tend to “stack” like bricks and may not adapt further. This is the case with Design No. 11 shown in Fig. 4. Here we have 36 building blocks, which are one-story high. The evolution process starting with such a fit and ordered design is not able to produce a much better solution. However, much more interesting patterns occur when the evolution starts with poorer designs.

As is shown in Fig. 23, evolutionary processes can form both one-story as well as more complex building blocks that are two or more stories high. In Fig. 23, the building block has been identified based on the similarities of the one- and two-story substructures occurring in both designs. It is visible that beam types and bracing types are very similar (they differ slightly but the general pattern can be identified) within each building block group. For example, Building Block Type I consists of a story of cells containing only X and simple X bracings. Building Block Type III includes two-story substructures in which outermost cells contain appropriately arranged K and V bracings. When we look back to Figs. 6, 13, and 16, it can be noticed that very similar patterns occur when the evolution starts with Population Nos. 1, 2, and 4.

The left design shown in Fig. 23 represents the best design obtained during short-term experiments, whereas the other one is the final solution obtained after 2,500 generations.

Evolution was able to create higher-level building blocks that were next used in different places of the steel skeleton system. Even more surprising, evolution has “learned” to evolve different types of substructures in various parts of the building structure (see Fig. 23). A more detailed analysis of the discovered emergent patterns can be found in Kicinger et al. (2002).

Summary and Conclusions

Evolutionary computation is becoming a paradigm that is increasingly attractive for civil and structural engineers. It reflects the ongoing transformation of computing in civil engineering from mostly analysis to more holistic aspects of design, including conceptual design, integrated design, etc. The occurring paradigm shift creates new challenges for researchers interested in closing the existing gap between the theoretical evolutionary computation research in computer science and the needs of practicing civil engineers.

General Research Findings

The reported work is a part of a large-scale research effort on Information Technology in Civil Engineering being conducted in the Information Technology and Engineering School at George Mason University. It is also a continuation of the previous research of the second writer (Arciszewski 1986; Arciszewski et al. 1994) in the area of structural systems in tall buildings. The paper provides experimental results from an exhaustive parameter search of short-term runs (up to a few hundred generations) conducted using an evolutionary computation support tool called Inventor 2001. Both qualitative as well as quantitative results are presented and discussed. In particular, the writers investigated the influence of various evolutionary computation parameters (mutation and crossover rates, population size, quality of initial parents) on the final outcomes produced by Inventor 2001. The importance of the symmetry requirement on the performance of the evolutionary design was a subject of the writers’ research interest as well and confirmed the traditional belief that structural systems should be symmetric. The paper also reports results of long-term evolutionary design experiments (at least a few thousand generations). A limited number of such experiments were performed, due to their high computational demands. However, the results of these experiments are promising and confirm and extend the previous findings obtained from short-term experiments.

The conducted research has demonstrated that Inventor 2001, an evolutionary computation support tool, is useful for exploring design representation space of steel skeleton structures in tall buildings, and for searching for novel design concepts, which may gradually emerge from simpler substructures being evolved by the system. The evolved multistory substructures form highly fit “building blocks,” which is in agreement with the building block hypothesis initially proposed by Holland (1975).

Experimental Setup Recommendations

The reported study has produced recommendations regarding “tuning” evolutionary design support tools based on the results of a large number of experiments performed. Specifically, it has identified recommendations regarding the rates of mutation and

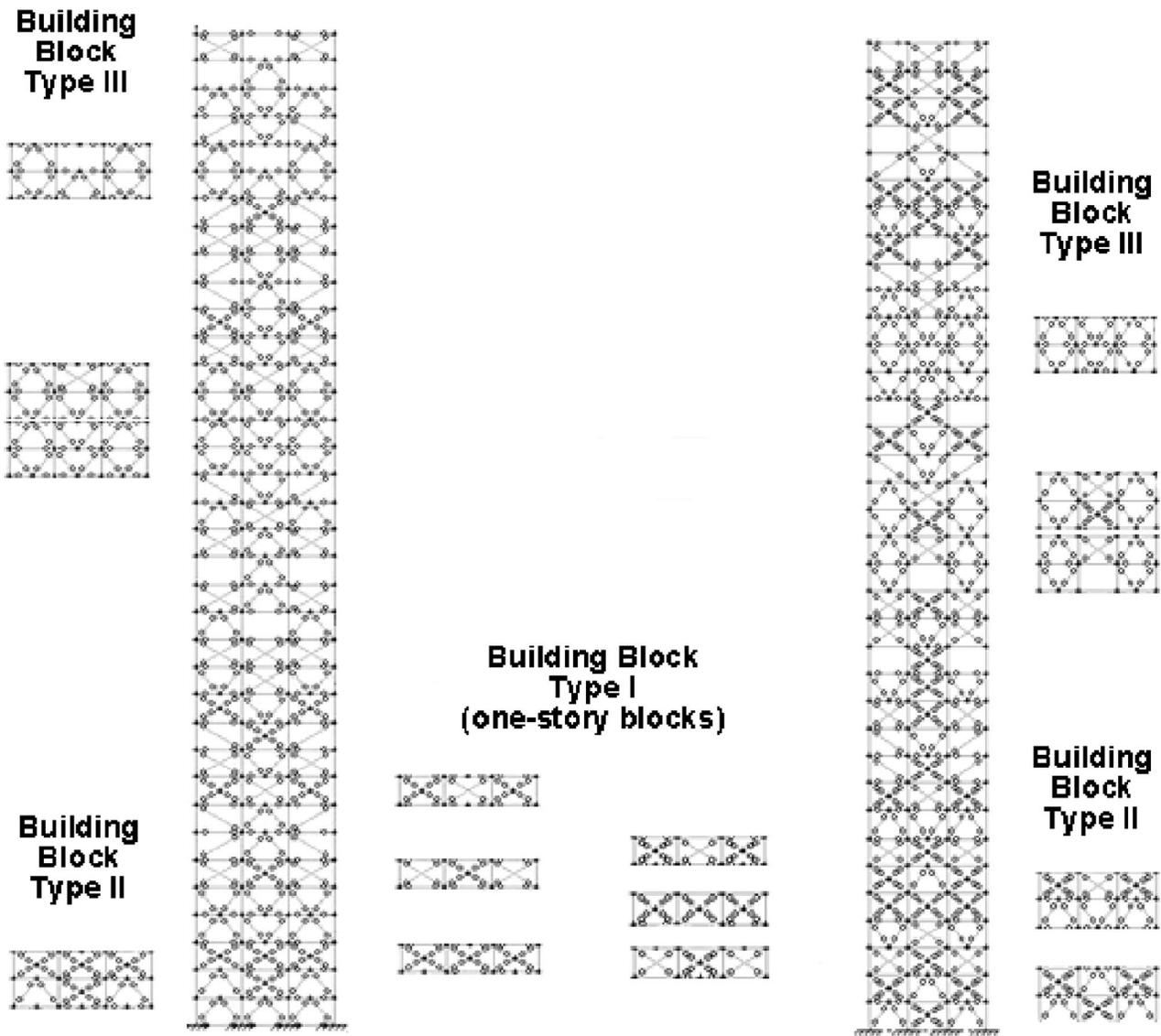


Fig. 23. Emerging substructures in evolving designs after 100 generations (left) and after 2,500 generations (right)

crossover (low rates of mutation up to 10% combined with crossover rates up to 50%, or randomly chosen mutation and crossover rates every generation) as well as choosing “optimal” values for population size (larger population sizes generally yield better results), number of generations (longer runs of up to a few thousand generations improve results by a few percent), etc. The reported results have been obtained for a particular domain (steel skeleton structures of tall buildings). However, there is a good possibility that they could be generalized to other structural engineering domains, although that might require more comparable experiments in various domains. The other general conclusion is that EC parameters working well for short-term runs should also perform quite well in longer EC design processes. Hence, the users of EC tools should first find the “optimal” parameter rates for their application domain using short evolutionary runs and/or the writers’ suggestions reported in the paper, and then run the actual long-term evolutionary processes. This practice should limit the time and effort required for conducting long-term evolutionary design processes.

The paper also presents the writers’ findings considering the importance of symmetry in evolutionary design. Results from the

conducted comparative experiments with and without the symmetry requirement suggest that symmetric designs are, on average, better by 1.5% after 100 generations (this study was conducted only for short-term runs). Hence, evolutionary design confirms traditional design practice, where the vast majority of designed structures are symmetric.

Emergence and Structural Design

The conducted experiments revealed the emergence of complex configuration patterns within the evolving structural systems. For example, in the experiment described in the Emergence section, after 92 generations and 1,380 structural designs produced, multistory substructures, or building blocks, appear in steel structures. These building blocks are in the form of combinations of K and V bracings located in the adjacent cells and forming two-story-high X trusses. They look similar to multistory “horizontal trusses” or outrigger trusses in belt truss systems (Arciszewski 1986), whose function is to redistribute wind forces, sending them to the outer columns and reducing in this way their magnitudes. Also, some form of “specialization” of these building blocks in various parts

of the building has been observed. These unexpected results seem to confirm our understanding of structural shaping of steel skeleton structures of tall buildings. Also, they seem to suggest that evolutionary design experiments not only may produce new structural concepts utilizing emerging building blocks, but could also produce a general knowledge about design for a given class of structural systems. An evolutionary design support tool as a design knowledge acquisition tool is a new and fascinating possibility, although it is too early even to speculate about its feasibility.

Data Analysis and Visualization Issues

The conducted research has revealed the importance of data visualization in evolutionary design, particularly when the number of attributes is on the level of hundreds, or thousands, and at least hundreds of generations are considered to identify trends and lines of evolution. Unfortunately, there are no commercial data visualization tools developed specifically for dealing with evolutionary design data, although several experimental tools discussed in Arciszewski and De Jong (2001) offer hope that such commercial tools will emerge soon. The research revealed a need to develop data visualization tools with several major functions, including: (1) monitoring and comparing changes of various attributes through many generations; (2) monitoring the evolution of the individual parent designs through their children; and (3) monitoring the dynamics of changes occurring at the individual generations. Also, data visualization should be combined with visualization of the design concepts being gradually evolved to provide a designer with an intuitive understanding of the entire evolutionary design process. This last aspect may be decisive to attract practicing designers to the evolutionary design tools.

Evolutionary computation in civil engineering applications is a fascinating emerging research area, which is still not fully understood in terms of its extent and priorities. The writers hope that this paper will stimulate a good discussion, which will result in better understanding of this new research area and will help us to continue our research.

Acknowledgment

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