GENETIC ALGORITHM APPLICATION IN STRUCTURAL ENGINEERING

1. INTRODUCTION

Applications of artificial intelligence are widely spread in last decades. Artificial intelligence is the branch of computer science that is concerned with the automation of intelligent behavior of human being. Genetic algorithm has attained considerable interest as a procedure that mimics the process of natural selection and survival of the fittest beside the neural networks which is inspired by the organization and functioning of the biological neurons and expert systems that are a simulation of expert reasoning. Genetic algorithms have been developed by John Holland, his colleague and his students in the University of Michigan. Its applications are widely spread in the current and last decade in the field of search and optimization.

The area of structural optimization has been and continues to be an active area of research. Improving the efficiency of numerical procedures, locating the global optimum, including realistic definitions of design variables, and handling wider class of problems are topics of most importance. Many difficulties arise in the optimal structural design using traditional mathematical methods as the existence of large number of design variable together with extensive constraints in addition to the probability of converging to locally optimal regions. On the other hands and for multiobjective optimization, the objectives to be achieved may frequently conflict with each other. In this case, no single ideal solution exists, which simultaneously satisfies the decision-maker across all criteria. Heuristic algorithms seemed to be suitable for solving the complicated problem of structural optimizations. Among the different techniques of evolutionary algorithms (genetic programming, simulated annealing, differential evolution, tabu search, etc), genetic algorithms were reported as the most common in engineering optimization practice (**Jones et al (2002)**, **Hrstka et al (2003)**).

The application of genetic algorithms to the solution of optimal structural design problem was early done by **Goldberg and Santani (1986)**. Great attention is then directed toward the development of genetic algorithm based optimization procedures and tools in different fields. The optimal design of steel trusses and frames attracted the majority of research especially in the early developments (**Rajeev and Krishnamoorthy (1992), Jenkins (1992), Coello (1994), Maher et al (1995), Galante, M. (1996)**). Steel design benchmark problems were applied in that work to make developments and enhancements on the procedures and techniques of genetic algorithms. Miscellaneous fields then attracted the application of genetic algorithms in different areas of optimum structural design. Additional investigations were made on the optimum steel design (**Chen and Rajan (1999), Nanakorn and Meesomklin (2001),Ali et al (2003)**) and optimal design of concrete structures (**Rafiq and Southcombe (1998), Maruyama et al (2001), Catallo (2004))**. As relatively modern structural applications, fields as the optimization of composite laminates (**Venkataraman and Haftka (1999)**, **Grosset et al (2002), Lin and Lee (2004)**) and structural control (**Arfiadi and Hadi (2000), Ahlawat and Ramaswamy (2003), Park et al (2004)**) also attracted the research on genetic algorithm application. Application of genetic algorithms extended to many other fields as the damage detection of structures (**Friswell et al (1998), Ratnam and Rao (2004)**), design of floor systems (**Miles et al (2001)**) and topology design (**Wang and Tai (2004)**). Research on the structural application of genetic algorithms extends over recent years as investigated in the literature.

In the present article, a review of genetic algorithm and its application to the field of structural engineering are presented. AT first, a brief introduction to genetic algorithm is presented including definitions, operators and categories. The genetic algorithm as being a member of optimization techniques and evolutionary algorithms is also discussed. Different structural applications of genetic algorithms in the optimization of steel structures, concrete structures, structural modeling, composites and structural control are then demonstrated. Finally, conclusions are extracted and fields of future developments are suggested.

2. OVERVIEW OF GENETIC ALGORITHM

In this section, brief description of genetic algorithm including the basic definitions of genetic algorithms and the main operators used in their development. Categories of genetic algorithms are discussed and the position of such technique among optimization techniques and evolutionary algorithms is illustrated

2.1. Definition of Genetic Algorithm

Genetic Algorithms are defined as search algorithms based on the mechanics of natural selection and natural genetics (**Goldberg (1989)**). They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. Genetic algorithms have been developed by John Holland, his colleague and his students in the University of Michigan. Genetic algorithm is a class of artificial intelligence (AI) which is defined as the branch of computer science that is concerned with the automation of intelligent behavior. Artificial Intelligence is a multi disciplinary field that encompasses computer science, neuroscience, Philosophy, Psychology, robotics and linguistics; and devoted to the reproduction of the methods or results of human reasoning and brain activity. It includes artificial neural network which imitates the organization and functioning of biological neurons, natural languages, expert systems and too many disciplines in addition to genetic algorithms.

A genetic algorithm approaches the solution of a given problem by taking a set of individuals (parents) and performing operations (crossover) on them to produce a new set of individuals (offspring). Selection is then takes place among the population of parents and offspring letting certain individuals (the fittest) to survive into the next generation. Although randomness plays a large rule in order to avoid stagnation in the population's evolution, ideally the offspring should eventually become better (i.e. fitter) (**Ignat (1998))**. Simulation of genetic algorithm procedure is shown in Figure (1) and flow chart of its application is shown in Figure (2).

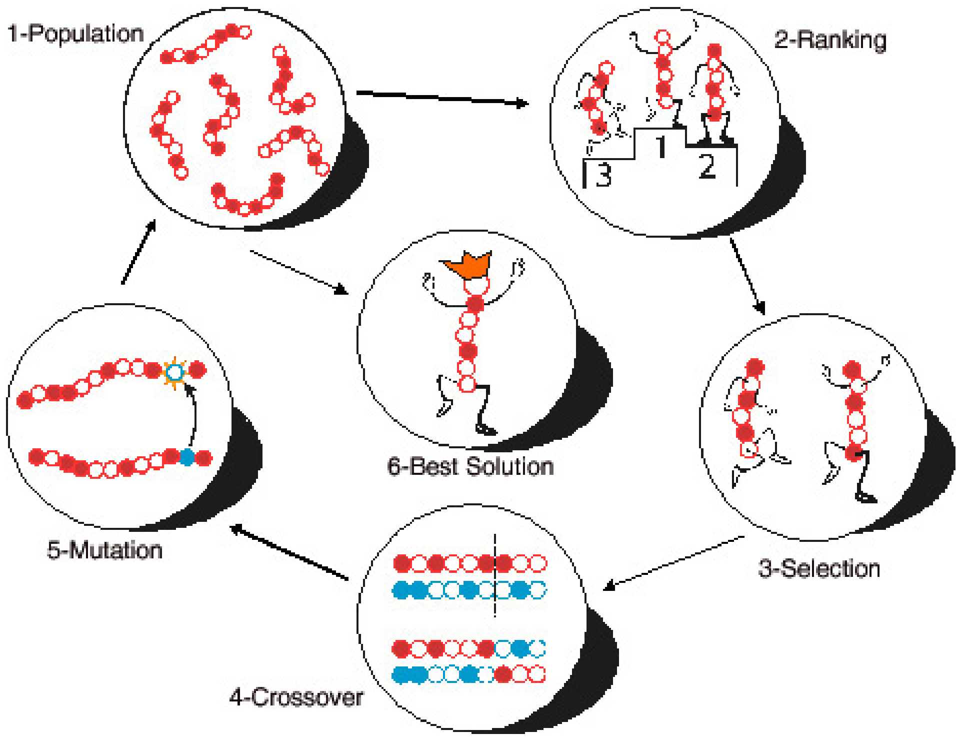


Figure (1) Simulation of Genetic Algorithm Procedure

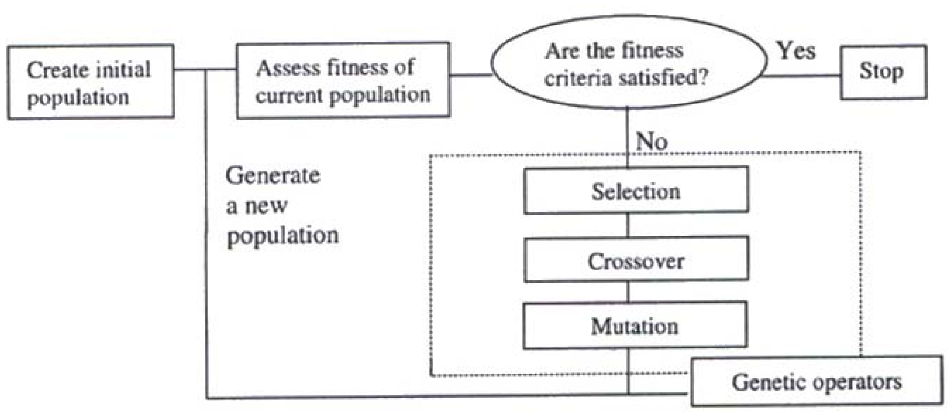


Figure (2) Systematic representation of Genetic Algorithms (**Miles et al (2001)**)

Common terms used in the definition and the development of genetic algorithm are listed below:

- ☑ ***A population*** is a set of chromosomes at specified generation which represent a subset of solution space

- ☑ ***A chromosome*** is a data structure that holds a "string" of task parameters, or genes. This string may be stored, for example, as a binary bit-string (binary representation) or as an array of integers (floating point or real-coded representation) that represent a floating point number. This chromosome is analogous to the base-4chromosomes present in our own DNA. Normally.

- ☑ ***A gene*** is a subsection of a chromosome that usually encodes the value of a single parameter.

- ☑ ***An allele*** is the value of a gene. For example, for a binary representation each gene may have an allele of 0 or 1, and for a floating point representation, each gene may have an allele from 0 to 9.

- ☑ ***The fitness*** of an individual is a value that reflects its performance (i.e., how well solves a certain task). In engineering optimization the fitness usually represents the objective function to be maximized or minimized.

- ☑ ***A genotype*** represents a potential solution to a problem, and is basically the string of values chosen by the user (Identical to chromosome).

- ☑ ***A phenotype*** is the meaning of a particular chromosome, defined externally by the user. It represents the solution in problem space corresponding to the chromosome

To clarify the definitions mentioned and illustrate the representation of real world engineering optimization problem using genetic algorithm the traditional 10-bar truss (presented in **Rajeev and Krishnamoorthy (1992), Galante (1996)**, **Turkkan (2003)**, .. etc.) representation is discussed. In this example, the truss, as shown in Figure (3), contains 10 bars and the problem is sizing problem such that the design variables are the cross sectional area of the truss members. Thus the ***chromosome*** must contain 10 ***genes***, each map to a specified member cross section. As commercial available steel cross sections are limited, discrete values rather than continuous are included according to given tables. If 16 different cross sections (Table.1) are selected to be applied to the design of the truss (**Rajeev and Krishnamoorthy (1992)**) and each cross section is numbered, 4 binary digits are needed to represent the section number. Thus 40 bits are required to represent the cross section of the truss members (10 members $\times$ 4 bits/member). As shown in Figure (4), the phenotype contains the cross sections of different members and the genotype is the binary representation of section number of each member while the population is the set of solutions in single generations. In the truss example, the fitness is defined as the weight (to be minimized) of the truss composed of selected members and constraints are applied in terms of member stress, buckling, and structure deflection.

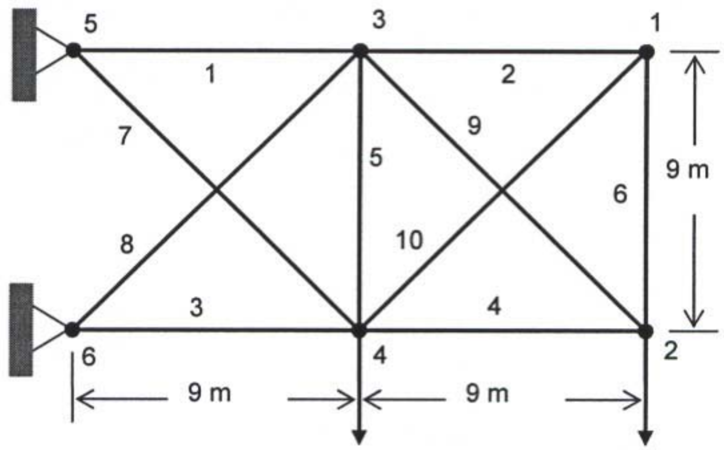


*Figure (3) The 10 bar truss example (**Turkkan (2003)**)*

Table (1) Discrete cross section area of steel sections used

Section No.	*Cross section Area*	*Binary Representation*
0	1.62	0000
1	1.80	0001
2	1.99	0010
3	2.13	0011
4	2.38	0100
5	2.62	0101
6	2.63	0110
7	2.88	0111
8	2.93	1000
9	3.09	1001
10	3.13	1010
11	3.38	1011
12	3.47	1100
13	3.55	1101
14	3.63	1110
15	3.84	1111

	1	2	3	4	5	6	7	8	9	10	Member
Phenotype ⇒	3.13	1.80	2.38	2.38	1.99	3.13	3.84	2.93	1.80	2.88	area
	10	1	11	11	2	10	15	8	1	7	Section Number
								Gene ⇓			
Chromosome (Genotype) ⇒	1010	0001	1011	1011	0010	1010	1111	1000	0001	0111	

Population

0001	1110	1011	0010	1110	1010	1110	1010	0101	0010
1101	0010	0100	1011	1011	1010	1011	0001	1011	0011
0101	0011	0111	1010	1001	0101	1100	0010	0101	0000
1111	1011	1110	1001	0101	1011	1011	1000	0100	1011
0010	0011	0100	1010	0101	0100	0111	1010	0100	0000
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
0001	0010	0111	1011	0101	0010	1011	1010	1011	1011

Figure (4) Coding of the 10 bar truss example

After coding of design variables, evolution is a process that operates in chromosomes rather than on the biological creature they encode (**Wang and Chen (1996)**) which makes genetic algorithms behaves as a blind search. Five main basic components are necessary for developing a genetic algorithm based optimization (**Gen and Cheng (2000), Koza (1992)**)

1- A genetic representation of solutions to the problem
2- A way to create an initial population of solution
3- An evaluation function rating solution in terms of their fitness
4- Genetic operators that alter the genetic composition of children during reproduction
5- Values for the parameters of genetic algorithms

The methods by which encoding of design variables ca be classified as follows: (**Gen, M., and Cheng, R. (2000),**)

- ☑ Binary Encoding
- ☑ Real- Number Encoding
- ☑ Integer Or Literal Permutation Encoding
- ☑ General Data Structure Encoding

2.2. Operators of Genetic Algorithm

A simple genetic algorithm that yields good results in many practical problems is composed of three operators; namely reproduction, crossover, and mutation explained as: **Goldberg (1989)**

Reproduction is a process in which individual strings are copied according to their objective function values, F (biologists call this function the fitness function). Intuitively, we can think of the function F as some measure of profit, utility, or goodness that we want to maximize. Copying strings according to their fitness values means that strings with a higher value have a higher probability of contributing one or more offspring in the next generation. This operator, of course, is an artificial version of natural selection (survival of the fittest) among string creatures. The selection criteria chosen can be one of the following (**Gen and Cheng (2000),**)

- ☑ Roulette Wheel Selection
- ☑ Tournament Selection
- ☑ Steady- State Reproduction
- ☑ Ranking And Scaling
- ☑ Sharing

Selection methods were discussed elsewhere (**Goldberg (1989)**). There are at least two reasons for the choice of tournament selection. First, tournament selection increases the probability of survival of better strings. Second, only the relative fitness values are relevant when comparing two strings. In other words, the selection depends on individual fitness rather than ratio of fitness values. **Chen and Rajan (1999)**.

Crossover is an operator used to produce two offspring from the selected parents. To select the parents for crossover, from the new population, a random number in the range 0 and 1 is generated. If this number is less than the probability of crossover, then the chromosome is selected for crossover (**Ahlawat and Ramaswamy (2002-a)**). Several crossover techniques are established for binary coded genetic algorithm between which the commonly used types can be listed as (**Hasancebi and Erbatur (2000)**):

➊ *Single-Point Crossover*.

Single point crossover is the first technique used in genetic algorithm and the most commonly used one. In single point crossover, a position is randomly chosen and then the two parents are exchanged at his point to form two new children (individuals). A schematic representation of single-point crossover is illustrated in Figure (5)

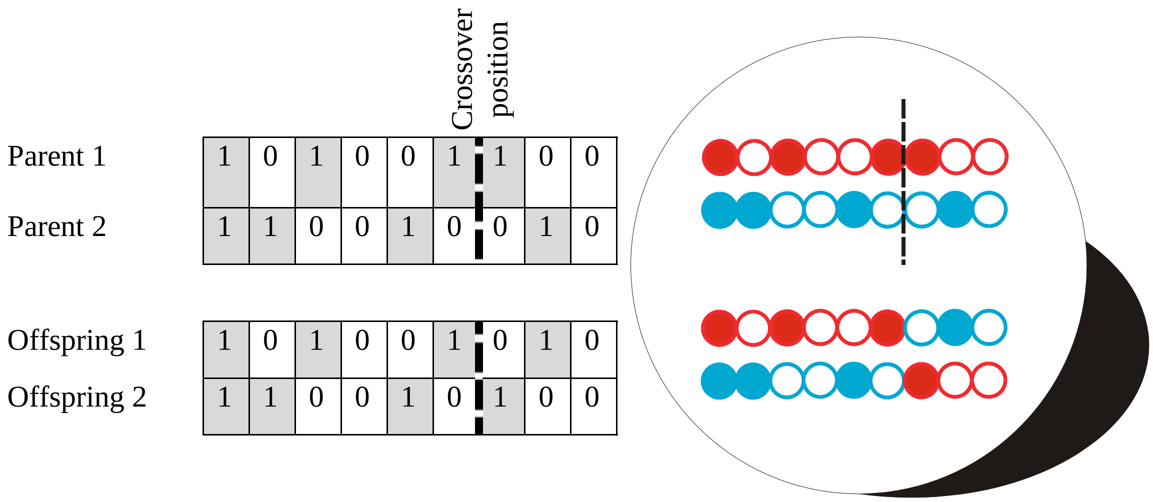


Figure (5) Single-Point Crossover

❷ *2-Point Crossover*.

Individuals (parents) are cut at two randomly selected positions and exchange of bits is made between both the inner portion between the two points or outer points as shown in Figure (6)

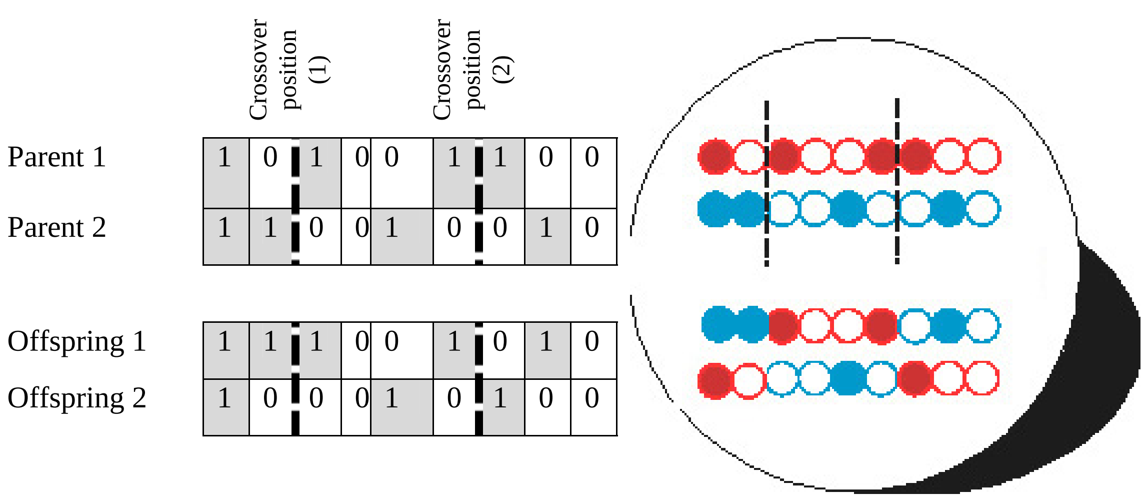


Figure (6) Two-point crossover

❸ *Multi-Point Crossover*.
More than two points are selected between them; the string bits of the parent chromosomes are then cut and exchanged.

❹ *Variable to variable Crossover*.
At first the overall chromosome is decomposed into substrings representing different design variables. Single point crossover is then performed between each corresponding substring.

❺ *Uniform Crossover*.
Uniform crossover generates random bit string of the same length of the parents chromosome called the crossover mask. The new child is then generated such that at positions where there is 1 in the mask, genes are carried from the first parent, and at positions where musk contains 0, genes are copied from the second parent. The second child individual can be created using another new mask or by using the complementary of the first mask.

For real coded GA, several crossover techniques are available such as the arithmetic cross over, guaranteed average cross over, and heuristic cross over (**Arfiadi and Hadi (2000).** Evaluation of different crossover techniques used in genetic algorithm were evaluated via the application to steel truss optimization problems by **Hasancebi and Erbatur (2000)**. Single point crossover, two point crossover, multi-point crossover, variable to variable crossover and uniform crossover are the first five techniques that were first illustrated and evaluated. Two truss sizing optimization (the traditional ten meber plane truss and 25-bar space truss) with two load cases for each were examined to illustrate the efficiency of the evaluated and suggested techniques. The developed computer program called GAOS (Genetic Algorithm in Optimization of Structures) uses the roulette wheel selection in binary coded GA with crossover and mutation probability 90 percent and 0.5 percent, respectively. The two point crossover technique was reported to be the best technique in exploiting the solution of problems among the tested five traditional techniques. Two additional techniques were developed as a result of the analysis of previous results. The first technique called the mixed crossover at which the 3-point crossover is first performed to achieve a thorough exploration of the design space, then the single-point crossover is applied to dominate an increased exploitation search, and finally the 2-point crossover is activated to provide fully exploitation search. The direct design variable exchange crossover is also suggested in which each design variable (substring) is directly and separately exchanged between paired individuals according to a probability function. In addition to the previously discussed truss examples, another large example of 72 bar space truss problem was investigated to evaluate previous and proposed techniques. The proposed methods of crossover proved good estimation of the optimum solution with emphasize on the direct design variable exchange as the method that produced the best solution.

Mutation: The mutation operator as shown in Figure (7) introduces new genetic structures in the population by randomly changing some of its building blocks, helping the algorithm escape local minima traps (**Hamada et al (2002)**)

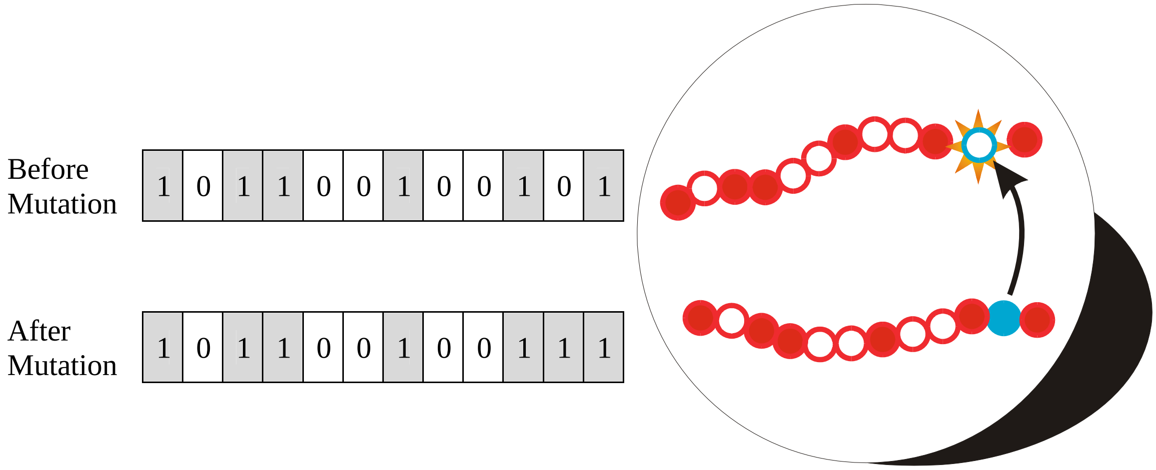


Figure (7) Mutation

2.3. Genetic Algorithm as an Optimization Technique

Optimization, as shown in Figure (8), is defined as the process of adjusting the inputs to or characteristics of a device, mathematical process, or experiment to find the minimum or maximum output or result (**Haupt and Haupt (1998)**). The input consists of design variables, the process is known as the cost function, objective function or fitness function, and the output is the cost or fitness.

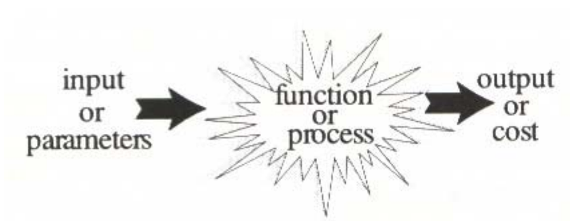


Figure (8) Diagram of optimization process (**Haupt and Haupt (1998)**)

Among the categories of optimization problems shown in Figure (9), the structural optimization problems have their special nature. The main features of engineering optimal design problem can be demonstrated as:

- ☑ The design variables of structural optimization problems may be continuous such that they can have any value in the domain as encountered in the problem of shape optimization of structures for which the coordinates of joints can occupy any coordinates. On the other hands, most of problems encountered in the field have discrete design variables. As an example, reinforcement bars have specific commercial diameters and structural steel sections are limited to specified tables.

- ☑ Most of structural optimization problems are heavily constrained. Several limits are specified for stiffness, strength and stability conditions

- ☑ The structural optimal may be single-objective or multi-objectives. For several cases of optimal steel design are single objective concerning the minimization of total structure weight (**Baumann and Kosty (1999)**). Multi-objective application frequently arisen as the optimization of Minimum Weight and minimum Strain energy done by (**Cheng and Li (1997)**) and the optimization in terms of the minimization of maximum peak displacement, the minimization of maximum peak acceleration, and the minimization of maximum peak rotation presented by **Ahlawat and Ramaswamy (2003)**.

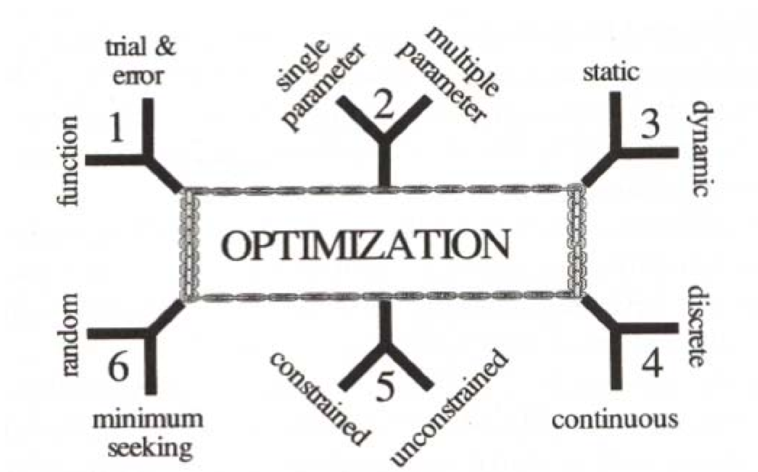


Figure (9) Categories of optimization algorithms (**Haupt and Haupt (1998)**)

Methods have been are derived for performing optimization that can be categorized into mathematical programming, optimality criteria and heuristic search as follows:

- ☑ ***Mathematical programming*** as Sequential Quadratic programming (SQP). To apply linear programming techniques to structural optimization, the relationship between the objective function and the constraints to the design variables have to be linearized. Application of the conditions necessary for solving nonlinear optimization problem is extremely difficult for most problems. The calculation of gradients and the solution of the correlated nonlinear equation are another difficulty. (**Camp et al (1998)**)

- ☑ ***Optimality criteria methods***. Typically, OC methods are based on continuous design variables. For the case where discrete variables are desired using OC methods A two–step procedure is typically used. First the optimization problem is solved using continuous variables. Second, a set of discrete values are estimated by matching the values obtained from the continuous solution which may shift the solution from optimum. (**Camp et al (1998)**)

- ☑ ***Heuristic search methods.*** In field of standard solution techniques for multi-objective or even single objective optimization, several factors; as large number of integer or binary variables, nonlinearity, stochasticity, non standard underlying utility functions and logical or non standard constraints and feasibility conditions complicate the solution of such problem. Although, these complications make the solution of optimization in specific problems using conventional methods so hard, the development of new techniques such as the meta-heuristics and evolutionary algorithms provides powerful tools to overcome such difficulties (**Jones et al (2002)**).

As the problem of structural optimization is discrete, constrained, multiple design variables, and having too many local optima, the heuristic search methods are optimal solution of such problems. Traditional mathematical methods usually fail to find robust solution of problems including the mentioned difficulties. An important aspect of genetic algorithms is that it is not necessary to know in advance how to solve a problem, it is only necessary to know how to rate potential solutions. This makes the genetic algorithm constitutes a powerful tool to deal with the optimum structural design problem which make more techniques were applied (**Wang and Tai (2004)**) and tools were developed to apply the GA concept to engineering optimum design problems (**coello and Christiansen (1999)**). The procedure used for genetic algorithm optimization is shown in Figure (10). Genetic algorithms are different from more normal optimization and search procedure in different ways (**Tesar and Drzik (1995)**, **Goldberg (1989)**, **Haupt and Haupt (1998)**)

- ☑ GA work with a coding of the parameters not the parameters themselves
- ☑ GA search from a population of points not a single point and thus makes the search space more wide.
- ☑ GA use Payoff (objective function) information, not derivatives or other auxiliary knowledge which may be so difficult in some situations.
- ☑ Optimize with discrete or continuous design variables
- ☑ GA use probabilistic transition rules, not deterministic rules.
- ☑ Provides a list of optimum solutions not a single one which gives the decision maker the flexibility to select from especially in multi-objective optimization at which the objectives to be achieved over these criteria may conflict with each other. In this case, no single ideal solution simultaneously satisfying the decision maker across all criteria (**Jones et al (2002)**).

Efficiency, reliability, accuracy and Robustness are common terms used to evaluate optimization techniques. Such terms can be defined as: (**Chen and Rajan (1999)**

- ☑ ***Efficient***: A methodology is defined as being efficient if it finds an acceptable solution with minimal computational effort.

- ☑ ***Reliable***: A methodology is defined as being reliable if it finds an acceptable solution regardless of the problem nuances or the starting point used.

- ☑ ***Accurate***: A methodology is defined as being accurate if it finds the best possible solution to a problem.

- ☑ ***Robust***: A methodology that is generally efficient, reliable and accurate.

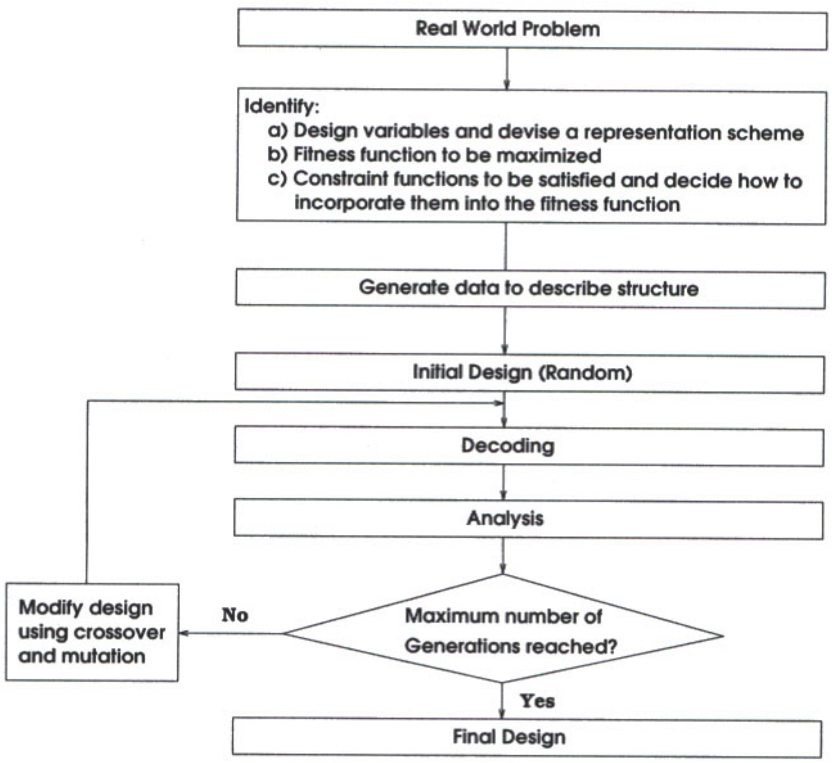


*Figure (10) Optimal Design Process Using Genetic Algorithm (***Coello et al (1997)**)

Structural design problems are usually heavily constrained as stresses, displacements, geometry and many other aspects of structures are subjected to constraints (**Jenkins (1997)**). In a highly constrained optimization problem such as structural optimization, maintaining feasibility can be a bottleneck for genetic search, and hence some sort of relaxation of constraints in the early stage of search is recommended (**Smith and Tate**

(1993)). Dealing with constraints is an important issue that attracts research to derive methods that make sure of feasibility of the final solution. A simple procedure can takes place as suggested by **Goldberg (1989)** by checking to see if any constraint is violated. For solutions that satisfy the constraints, fitness value is assigned while no fitness is assigned to infeasible solutions. The most common method of dealing with constraints for structural optimization problem is the penalty function method in which the constrained problem is transformed to unconstrained one by associating a cost or penalty with each constraint violation. If the original problem is defined as

Minimize $g(x)$

Subject to $b_i(x) \geq 0$ i = 1, 2, 3, … ,n

The problem can be transformed to be in the form

Minimize $g(x) + r\sum_{i=1}^{n}\Phi[b_i(x)]$

Where Φ is the penalty function and r is the penalty coefficient. Penalty functions are extensively derived and penalty coefficients are adjusted for constrained optimization problems **(Crossley and Williams (1997)**). Another method can be used to handle constraints, especially in case that the feasible region is very narrow and almost all individuals violate the constraints. The method is called the "***pulling back method***" in this method, when an individual violates constraints, this individual is moved is moved to the point that satisfies constraints (**Hiroyasu et al (2002)**)

2.4. Genetic Algorithm as an Evolutionary Strategy

Evolutionary algorithms are different computer algorithms based on the process of natural evolution. They imitate the biological evolution in nature and follow the concept of the survival of the fittest. The major kinds of evolutionary algorithms can be summarized as: (**Lagaros et al (2002)**, **Hrstka et al (2003)**, **Jones et al (2002)**)

- ☑ Evolutionary Programming
- ☑ Genetic Algorithms
- ☑ Evolution Strategies.
- ☑ Differential Evolution
- ☑ Simplified Differential genetic algorithm
- ☑ Simulated annealing (emulates the way in which a material cools down to its steady state)
- ☑ Integer Augmented Simulated Annealing (IASA) (a combination of integer coded genetic algorithm and simulated annealing)
- ☑ Real-coded augmented simulated annealing (RASA) (a combination of real-coded genetic algorithm and simulated annealing)
- ☑ Tabu Search draws in the social concept of 'taboo'

Genetic Algorithms are the most widely used type of Evolutionary computation methods as the evolution strategies, evolutionary programming and genetic programming. A wide survey including 115 articles concerned with the theory and application of multi-objective optimization using the so called meta-heuristics including genetic algorithms simulated annealing and tabu search has been performed by **Jones et al (2002)**. Figure (11), which demonstrates the frequency of articles collected in the period 1991-1999 in the three mentioned fields, illustrates the increase of developments indicating rise in their popularity.

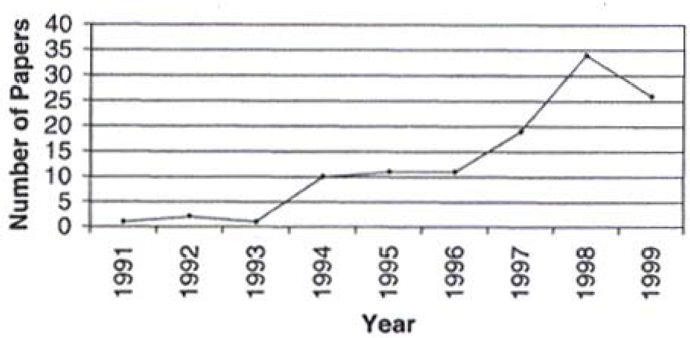


Figure (11) Article Frequency in the Period 1991-1999 in filed of Genetic Algorithm, Simulated Annealing, and Tabu Search (From **Jones et al (2002)**)

The categorization of collected articles by field of application is shown in Figure (12). Theoretical developments, which establish the basis of the theoretical foundations of the methods and develop the required procedures constitutes the majority of works as result of that such techniques are relatively new. After that, growing application to all field including civil, mechanical, electrical and industrial engineering is observed in addition to medical, environmental, and information technology applications.

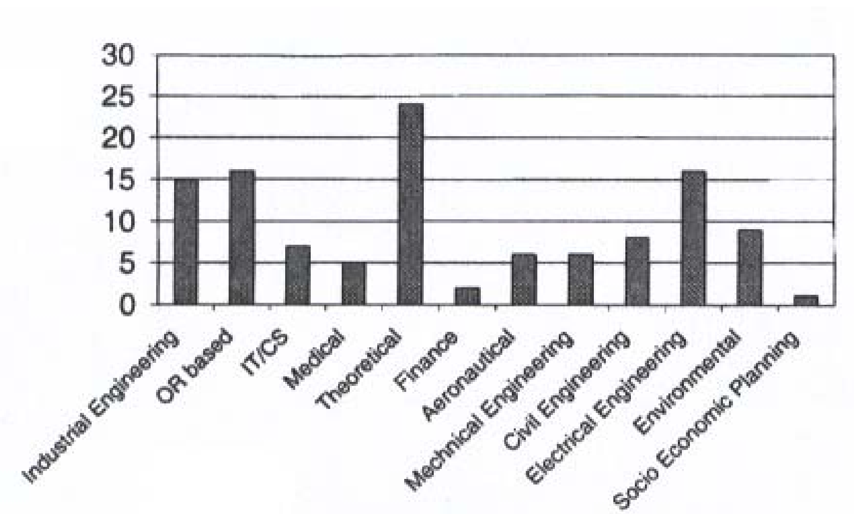


Figure (12) Break down of articles by application area in filed of Genetic Algorithm, Simulated Annealing, and Tabu Search (From **Jones et al (2002)**)

The following figure illustrates that the majority of applications surveyed are carried out using the genetic algorithm technique. While 70 percent of the articles utilize genetic algorithm, only 24 percent and 6 percent of articles use simulating annealing and tabu search, respectively. The distribution shown in Figure (13) reflects the popularity and flexibility of genetic algorithm as optimum search technique.

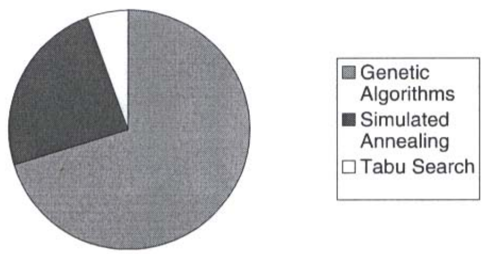


Figure (13) Break down of articles by primary method in filed of Genetic Algorithm, Simulated Annealing, and Tabu Search (From **Jones et al (2002)**)

Points concerning the strengths and weaknesses when applied to multi-objective optimization are also summarized. The main advantages of meta-heuristics are that these methods are mainly discrete as opposed to the conventional methods which are continuous in nature. The range of models developed in the area of meta-heuristics is another advantage over the other conventional methods which gives the methods generality and flexibility. Disadvantages reported for meta-heuristics are that the methods are not function optimizers that are aimed at finding good solution and not the guaranteed optimal solution. This disadvantage is does not add merits to conventional methods as the article reviewed deal with complex real world systems for which no guaranteed conventional solution exists. The sensitivity of meta-heuristic methods to large number of parameters set by the modeler is another disadvantage which makes the methods as poor black box more difficult to apply. The need to develop analysis techniques for the meta-heuristic methods for sensitivity analysis, Pareto efficiency checking and redundancy checking is certified. The majority of these techniques already exist for conventional methods.

Hrstka et al (2003) carried out a comparison of several stochastic optimization algorithms for the solution of some problems arising in civil engineering. The introduced optimization methods are: the integer augmented simulated annealing (IASA), the real-coded augmented simulated annealing (RASA), the differential evolution (DE) and simplified real-coded differential genetic algorithm (SADE). Each of these methods was developed for some specific optimization problem; namely the Chebychev trial polynomial problem, the so called type 0 function and two engineering problems; the reinforced concrete beam layout and the periodic unit cell problem, respectively. Detailed and extensive numerical tests were performed to examine the stability and efficiency of proposed algorithms. The results of our experiments suggest that the performance and robustness of RASA, IASA and SADE methods are comparable, while the DE algorithm performs slightly worse. This fact together with a small number of internal parameters promotes the SADE method as the most robust for practical use. Another iterative methods based on evolution were presented (**Manicharajah and Steven (2000)**). Other categories of genetic algorithm are evaluated and used to improve the convergion such as the genetic algorithms with punctuated equilibria defined as GA for which multiple populations are allowed to develop independently of each other and performing the genetic algorithm operations on each. Then migration is allowed by letting individuals selected randomly weighted by their fitness to be exchanged between once every certain number of generations (epoch) (**Ignat (1998)**).

3. STRUCTURAL AppLICATIONS OF GENETIC ALGORITHMS

Several characteristics exist in the structural design problem make the use of genetic algorithm suitable for structural engineering optimization which can be listed below (**Nanakorn and Meesomklin (2001)**):

1. In structural engineering optimization, the global optimum is always searched.
2. Design variables in engineering design are generally discrete
3. Structural optimization problem always contains constraints.

Experience with GA has indicated that more often than not, tuning the GA strategy and parameters can lead to more efficient solution process for a class of problems (**Chen and Rajan (1999)**). The simple GA while powerful is perhaps too general to be efficient and robust for structural design problems due to several reasons. First, function (or, fitness) evaluations are computationally expensive since they typically involve finite element analysis. Second, the (feasible) design space is at times disjointed with multiple local minima. Third, the design space can be a function of Boolean, discrete and continuous design variables. The existence of large number of design variables and constraints is an important difficulty that makes the feasible region is very narrow (**Hiroyasu et al (2002)**). In this section different applications of genetic algorithm to structural engineering are discussed. At first, statistics of the current literature is carried out to demonstrate the distribution of studies along last 10 years and the amount of work done in each field. A review of available literature categorized according to the field of application is then presented.

3.1. Statistics of Literature

The development of applications of genetic algorithms in the field of structural optimization is illustrated in this section. Figure (14) shows the frequency of structural applications using genetic algorithm during the last 10 years. It can be easily observed from the figure that the number of studies, at general, increases in last years such that more studies are observed during year 2004 than any previous year. It can be concluded that the interest of researchers on the genetic algorithm application increases and that extensive future work is expected.

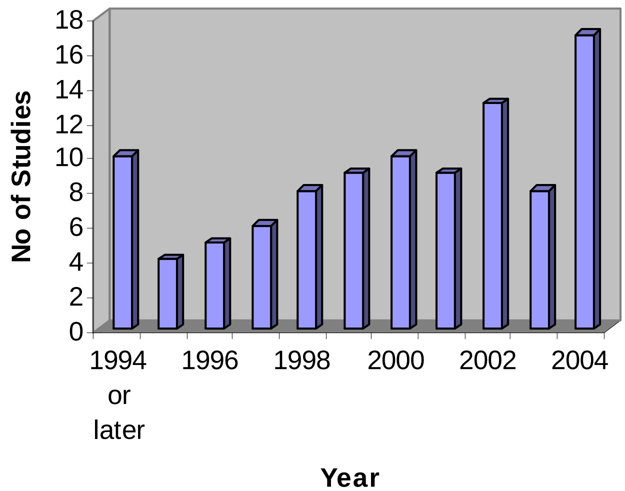


Figure (14) Frequency of Applications of Genetic Algorithm in Structural Optimization During the Last 10 Years

Break down of articles in structural optimization using genetic algorithm by the field of application is shown in figure (15). Four categories are considered constituting the main fields found in literature. As shown, steel design attracted the majority of studies such that 47% of work done was in field of steel frame and truss design. The rest of work is divided by other fields such that the design of concrete structures, structural models, composites and structural control show comparable divisions. The domination of steel design on other fields can be attributed to the nature of steel design problem in addition to that the early work on genetic algorithm structural optimization used the design of steel truss as bench mark problem

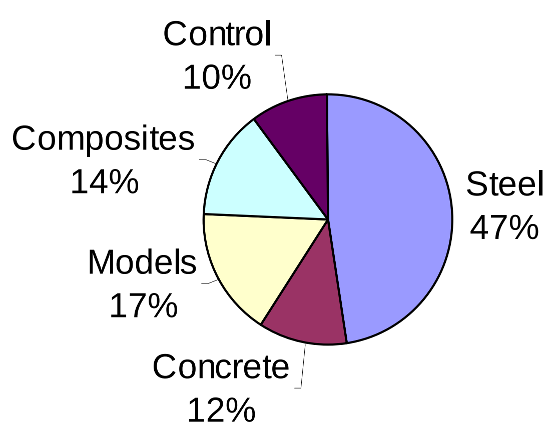


Figure (15) Break Down of Articles By the Field of Application

To illustrate the development and growth of genetic algorithm applications in structural optimization, Figure (16) shows the frequency of articles by the filed of application during the last 10 years. Comparing the early works in 1994 and later with the last years certifies the growth of application fields. In 1994 and later, design of steel structures is only studied by all research work while in 2004, all the five categories considered are present. In between and along the 10 years considered, the fields of application increases which illustrate the large development in the field of structural optimization using genetic algorithm.

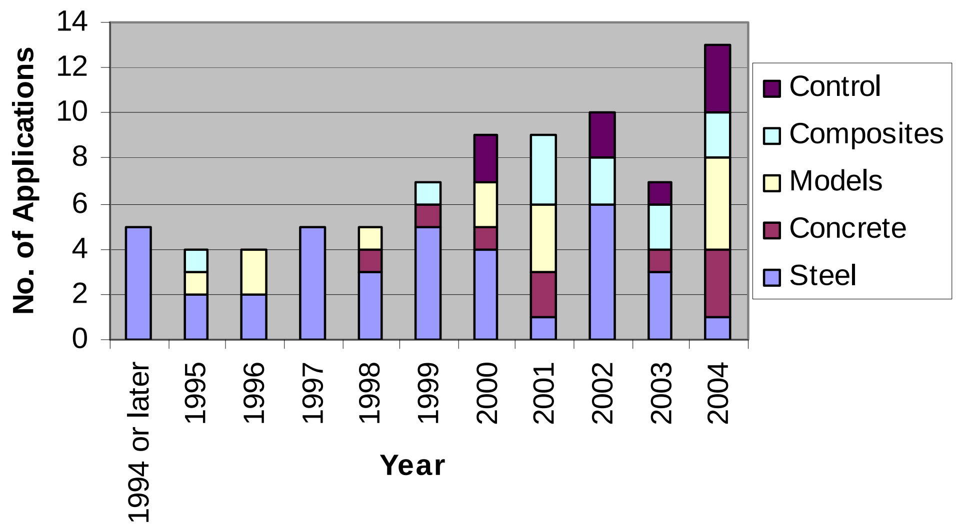


Figure (16) Frequency of Articles by Field of Application of genetic Algorithm During the Last 10 Years

3.2. Design of Steel Structures

Steel structure optimization is common as total weight optimization problems. With respect to design variables, sizing optimization, shape optimization, and topology optimization are common terms. The sizing design variables considered are either cross-sectional dimensions or available cross-section. The former can be described using continuous design variables since these dimensions can vary continuously. The latter is described in terms of integers (an integer index that points to a row in a table of available cross-sections). The table search is carried out by using a table of ordered available cross-sections with the lower and upper bound candidate cross-sections specified by the user. The shape design variables are the nodal locations. These are real design variables. The topology (boolean) design variables can be structural parameters such as the presence or absence of members, and presence or absence of fixity conditions at supports or connections. **Chen and Rajan (1999)**. Genetic algorithms were also incorporated into an environment for optimum design of plane frames by **Jenkins (1992)** and illustrated by an example of cable stayed bridge. Genetic programming was reported to be less problem dependent when applying to steel truss examples (**Yang and Soh (2002)**)

Rajeev and Krishnamoorthy (1992) applied the concept of genetic algorithm to optimal design of different steel truss examples. Minimization of total weight was considered as the target objective function while penalty was applied to take the constraint violation into account. The merits of using genetic algorithms as optimization tool for problems including discrete variables and its generality and ability to apply to design of steel trusses were discussed and verified (**Coello (1994), Coello et al (1994)**). **Maher et al (1995)** presented a gene approach to demonstrate design exploration as compared to search and applied the approach to the design of braced steel frames for buildings.

A procedure was developed for the combined sizing (**Camp et al (1998))**, shape, and topology design of space trusses (**Rajan (1995)**) defined by:

- ☑ **Sizing**: Cross sectional area of members was used as discrete or continuous values.
- ☑ **Shape**: Nodal coordinates are continuous design variables using hybrid natural approach.
- ☑ **Topology**: Boolean Design variables represented the existence, connectivity and support conditions of nodes.

Additional concepts were incorporated to accelerate conversions and reduce the computational effort. Large penalty terms were applied to the unstable structures and structures with no deformations while penalty coefficients were applied to structures whose performance constraints are not satisfied. In order to find better solutions, restarts were also used by generating the entire population randomly or letting the user specify the initial design variables. Zero force members are omitted from fitness calculations and chromosome history was saved and checked to avoid the fitness calculation of repeated chromosomes to reduce computation effort.

Cheng and Li (1997) presented a methodology of constrained multiobjective optimization problems (MOP) by integrating a Pareto genetic algorithm and a fuzzy penalty function method. The Pareto genetic algorithm proposed consists of the Pareto set filter and the niche as two additional operators in addition to the reproduction, crossover, and mutation to constitute five parts system. The Pareto set filter was applied to pool non-dominated points ranked 1 at each generation and drop dominated points in order to stop the loss of Pareto optimal points. Ranking was applied as a continuous labeling process such that at each generation non-dominated points (Pareto set) are selected and assigned rank 1. From the remaining population non dominated points are identified and assigned rank 2 and this process continues for rank 3, 4 and so on until the entire population is ranked. The feasible vector x* is defined to be a Pareto set if and only if there exists no feasible vector x such that

$$f_i(x) \quad \leq \quad f_i(x^*) \qquad \text{for all} \qquad i \in (1,2,........,m)$$

and

$$f_i(x) \quad < \quad f_i(x^*) \qquad \text{for at least one} \qquad i \in (1,2,........,m)$$

Pareto sets are solution for which no objective can be improved without detracting from at least one another objective. Any point in a pare to optimal set can become an "optimum solution" depending on the decision-makers opinion as MOP has no unique optimum that can simultaneously optimize all objectives as shown in Figure (17).

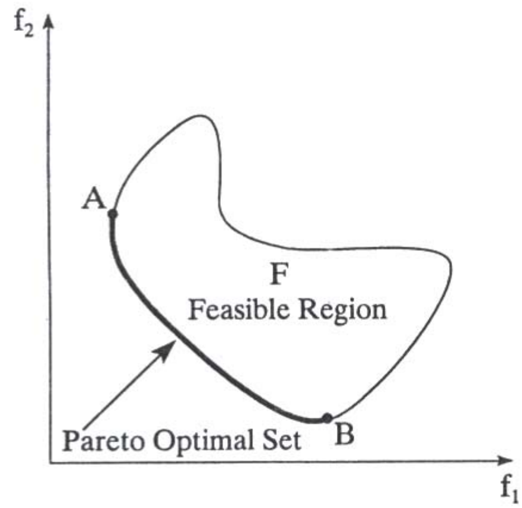


Figure (17) feasible Rejoin and Pareto set in objective space **Cheng and Li (1997)**

Niche technique prevents genetic drift and significantly distributes a population uniformly along a Pareto optimal set. In such technique an offspring replaces its parent if the offspring's fitness exceeds that of the inferior parents. This niche technique prevents the formation of a lethal and the reproduction of procedure is a steady state one. The revised penalty function method was reported to fail to work properly in a Pareto GA for constrained MOP. Thus, a fuzzy logic penalty function method was developed with a combination of deterministic, probabilistic and vague environments that are consistence with GA operation theory based on randomness and probability. Constraints were incorporated by the rules that (1) point's status as feasible or infeasible should be indicated by the function; (2) closer points to feasible zone will have more fitness; and (3) points closer to Pareto optimal set is assigned higher fitness values. Genetic algorithm with uniform crossover, crossover probability of 60 percent and mutation probability of 1 percent was applied. Sample cases of 4-bar pyramid truss, 72-bar space truss with two criteria (Minimum Weight, Minimum Strain energy) and four-bar truss with three criteria (Minimum weight, Minimum Deflection of two load cases). Weight minimization was achieved by using population size of 400 individual and chromosome length 60, 240, and 60 for the tree studied examples, respectively. For the second illustrated example shown in figure (18), the Pareto set filter identified the Pareto set shown in figure (19). it is clear that the most optimum design for weight (min. W) results in high strain energy while the most optimum design for energy (min. E) leads to unsatisfactory weight. The optimum solution of the problem (min. (W, E)) can be decided by the judgment of decision maker according to the relative importance of each objective. Numerical results certified that the Pareto GA applies is a powerful tool for a constrained MOP efficient, robust and exhibits global conversions.

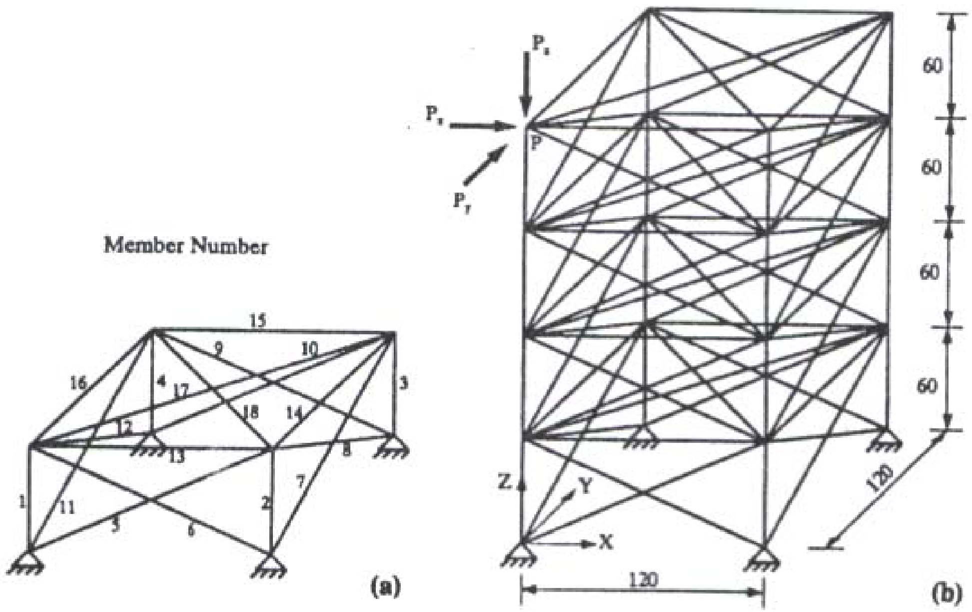


*Figure (18) 72–Bar Space truss example (**Cheng and Li (1997)**)*

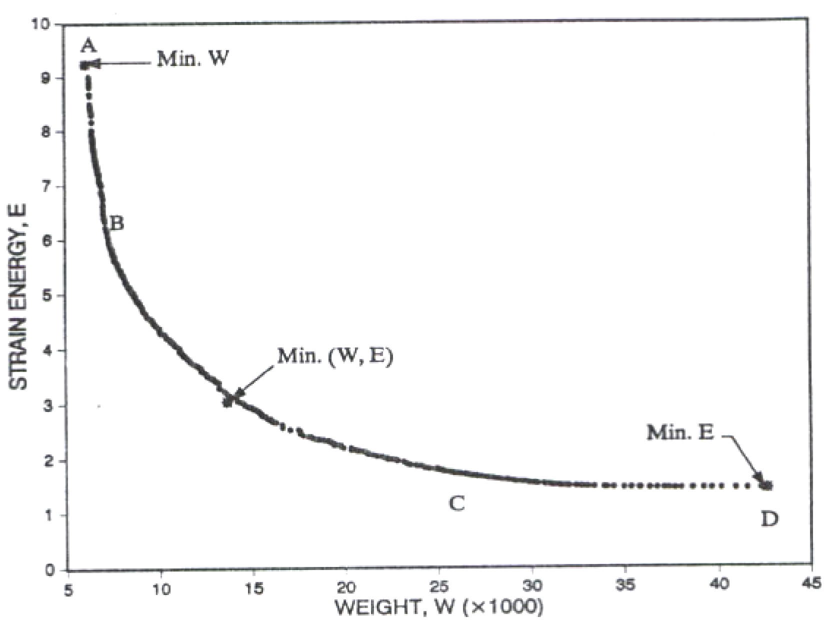


*Figure (19) Pareto Set Filter at Generation 500 of Revised Niche Method (**Cheng and Li (1997)**)*

Several techniques were applied also to optimum design of structures and illustrated by application to steel trusses as the data envelopment analysis (**Arakawa et al (1998)**). The development and implementation of genetic algorithm based methodology for automated design of discrete structural systems was presented by **Chen and Rajan (1999)**. Consideration of sizing, shape and topology optimal design of frames subjected to static and dynamic loads were carried out. Enhancements were made to the simple GA to increase the efficiency, reliability, and accuracy of the GA methodology for code-based frame design. Constraints were considered through an adaptive penalty function for which penalty weights are computed automatically and adjusted in an adaptive manner. Uniform crossover, tournament selection and elitist approach was used in reproduction of the applied binary coded GA with population 2n where n is the chromosome length. Two numerical examples were presented and solved using the proposed enhanced GA with crossover probability of 90 percent and mutation probability 3 percent. For the first example which constitutes a roof truss, the optimized weight was reported to decrease by 20 percent less than previous studies in case of sizing and 40 percent in case of adding topology optimization as result of the application of procedure enhancements in addition to reducing the computation time by about 13 percent. Comparisons with results from prior applications and solution of other examples proved that enhancements made to the GA adds well to the efficiency and robustness of the system

A technique for conditioning the components of the fitness statement using ranking and a graphical method for monitoring components of the rank based fitness function was presented and applied to the problem of design of steel structures(**Voss and Foley (1999)**). By utilizing generationally dependant non-linear rank based selection along with translocation crossover and intelligent mutation to maintain genetic diversity, the proposed algorithm was able to operate directly on a heuristic tree representation of the design variables. Performance and control of the evolutionary algorithm was demonstrated and discussed via a cantilever column example problem. The implementation of translocation and macro crossover was reported to be the main motivation for this study and the proposed evolutionary algorithm over the traditional genetic algorithms. Authors presented a general evolutionary algorithm where upon the solution space is effectively explored through probabilistic reproduction and fair participation of fitness function components throughout the evolutionary process. A graphical method for interactive algorithm tuning was also developed which allows the user's intuition to be readily incorporated into the selection process. The proposed enhancements were applied to the optimization of three dimensional, ten-segment, rectangular cantilever column for which the volume was considered as the objective function to be minimized. Constraints were introduced using penalty function concerning deflections, stiffness and shape in two directions. Two design variables are the dimensions of segments (h_x and h_y) were considered for each of the ten segments and the values for these variables are assumed to take on discrete quantities and thus, the problem contains 20 discrete design variables. The results indicated that the proposed evolutionary algorithm will scale well and allows a great deal of flexibility to deal with the complexities of multi-constraint optimization. It was emphasized that traditional binary representation is still possible, but may not be necessary depending on the problem and type of translocation crossover and mutation applied.

The optimum design of truss structures was implemented using genetic algorithms and compared with mathematical programming method by **Coello and Christiansen (2000)**. Compared with the best results in literature, as applied to two problems of 25-bar space truss and 200-bar plane truss, GA proved to generate better trade off and can be used as reliable numerical optimization tool. An adaptive penalty scheme that is free from the disadvantages of conventional penalty coefficients assignment was developed by **Nanakorn and Meesomklin (2001)**. The proposed penalty function was reported to be able to adjust itself during the evolution in such a way that the desired degree of penalty can be always obtained. The parameter used to justify the penalty weight was suggested as the ratio between the fitness value of the best infeasible members and the fitness value of the average feasible members. Application of the technique to several benchmark truss and frame problems certified the stability and robustness of the proposed methodology. The proposed method proved also that the solution is independent on the units used.

Krishnamoorthy et al (2002) discussed the object-oriented design and implementation of genetic algorithm core library consisting of all the genetic algorithm operators having an interface with the genetic objective function. Strategies were also suggested for member grouping for reducing the problem size. The concept of building such framework was based on the division of the genetic algorithm into a problem-independent genetic operations part and a problem dependent function evaluation part linked by the coding scheme and fitness evaluation. The developed framework called GALiLEO (Genetic Algorithm Library for Learning and Engineering Optimization) contained all commonly used selection, crossover, penalty handling and sharing procedures that can be linked to a variety of objective functions. Instead of using an external finite element program to perform the required analysis with file link with the framework, the framework was integrated with a specially developed finite element program, PASSFEM (Program for Analysis of Structural Systems using the Finite Element Method). The implemented library was tested on a number of large previously fabricated space trusses and the results were compared with previously reported values. Authors concluded that genetic algorithms implemented using an efficient and flexible data structure can serve as a very useful too in engineering design and optimization.

Genetic algorithm optimization procedure was applied to weight optimization of steel plane frames subjected to different load cases by **Torregosa and Kanok-Nukulchai (2002).** The scope of this study is limited to the weight optimization of plane frames under a specified loading. Discrete design variables are the standard commercial steel sizes for which a database of steel beam sizes is provided as the discrete variables. This work was reported to concern with the linear elastic analysis of the 2-dimensional frame and designing the members following the allowable stress design (ASD) procedure on the AISC code provisions. Only the member of the superstructure is subjected to optimization. Both elitist and non-elitist search procedures are used to optimize the total weight of steel frames. Crossover types used are 20- and 50-percent uniform. Single objective function (Weight) was used and constraints are incorporated into the fitness via penalty function representation. The procedure of suggested genetic algorithm optimization is shown in the flowchart of Figure (20).

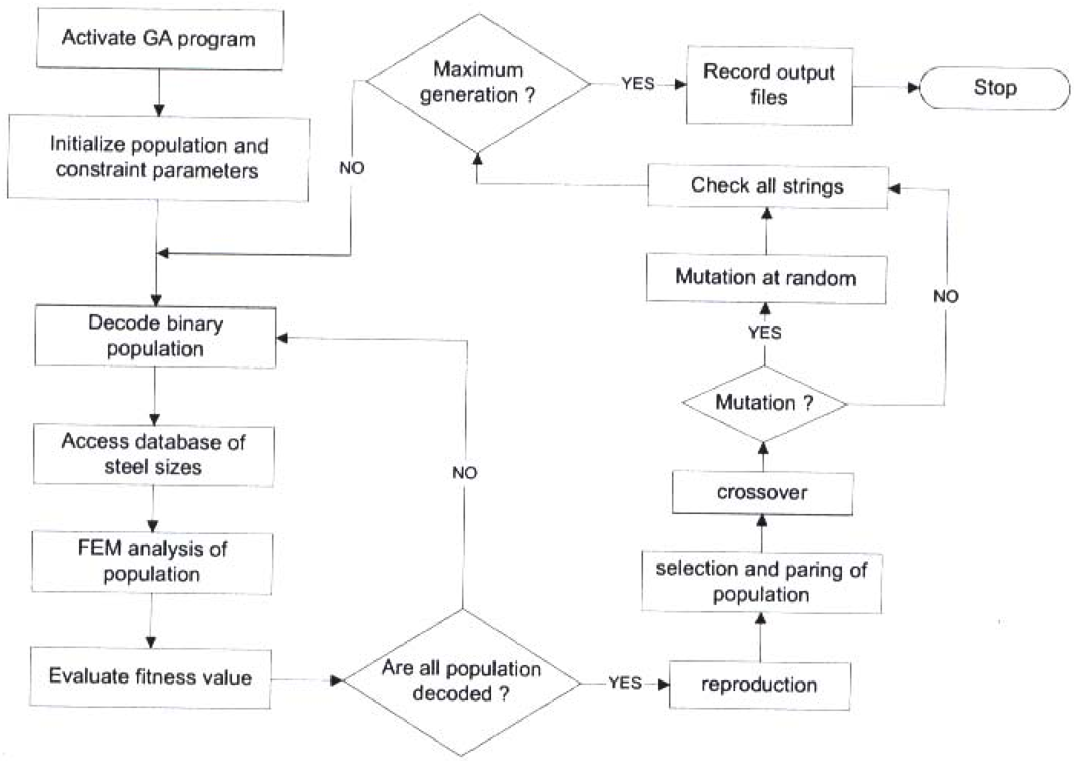


*Figure (20) genetic optimization procedure (***Torregosa and Kanok-Nukulchai (2002)***)*

Optimization result using population sizes 10, 20, and 40 are compared. Elitist search procedure showed superior results when compared to non-elitist for higher population sizes search because of its faster convergence rate. Two examples of 3-bay 6-story frame and 3-bay 3 story frames was introduced to illustrate the performance of the suggested methodology. Performance of non-elitist is superior when using lesser population sizes. To examine the performance of genetic algorithms, case studies are conducted by varying material groups and the results are compared with the results from other optimization techniques. Genetic optimization showed superior results when compared to other techniques especially to problems with few material groupings.

Lagaros et al (2002) investigated the efficiency of different evolutionary algorithms (EA) when applied to large scale structural sizing optimization problem. Hybrid methodologies combining genetic algorithms, evolution strategies and mathematical programming method of sequential quadratic programming (SQP) are also tested. The proposed hybrid approach was first applied to the academic problem of minimizing the volume of the three-bar truss and then applied to the minimization of weight of two practical steel frame examples. The first example is six story space set back frame containing 63 elements and 180 DOF subjected to gravity and lateral loads while the second is 20 story space frame contains 1020 members and 2400 DOF subjected to vertical and lateral loads. The proposed hybrid approach proved to be robust and efficient for structural optimization and that GA-SQP and ES-SQP converge well at a reduced computational effort compared to the SQP procedure. GA-SQP are reported to be so efficient in case of problems with bad initial designs due to the fast convergence GA toward the neighborhood of optimum

A methodology of optimum shape design of skeletal structures using genetic algorithm is proposed by **Shrestha and Ghaboussi (1998).** The generated structure can contain truss or beam elements or both and supports may be fixed, hinged or roller. Sizing, geometry and topology are the three aspects considered simultaneously in the proposed methodology. The evolved structure can acquire any shape within the physical design space provided that (1) the structure have any number of free nodes, fixed nodes or partially fixed; (2) members are chosen from set of discrete member sizes and (3) the structure may be subjected to static or moving; single or multiple loads including self weight of the structure. Weight of the structure is considered as the design objective function to be minimized with constraints including stress limits, slenderness ratio, minimum member length, maximum member length, member symmetry, node displacement and nodal symmetry. Binary coded genetic algorithm is used with multiple points crossover are customized in the proposed methodology. The proposed methodology is applied in two truss examples spanning 70 meters with different heights for optimum weight. Due to the complexity of the problem and the huge number of design variables encoding of the example problem contains too many digits as binary string reaching 25200 bits. Design variables included node and member information. Node information includes nodal active/inactive, nodal coordinates and support type. Member information includes member active/inactive, sector priority, member type and connection type. The space around each node was discretized into number of sectors, each possessing specific set of member properties and a measure of its priority with respect to other sectors as shown in Figure (21). The string representing the structure was made up of a fixed number of identical substrings, each corresponding to a specific node and member as shown in Figure (22).

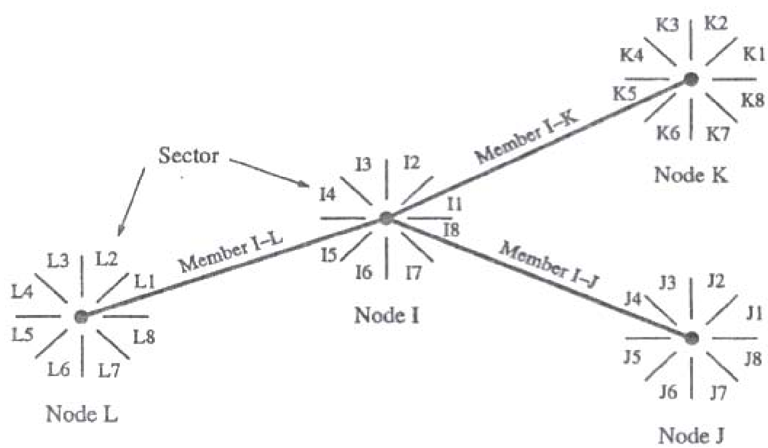


Figure (21) Sectorial representation of Topology (**Shrestha and Ghaboussi (1998)**)

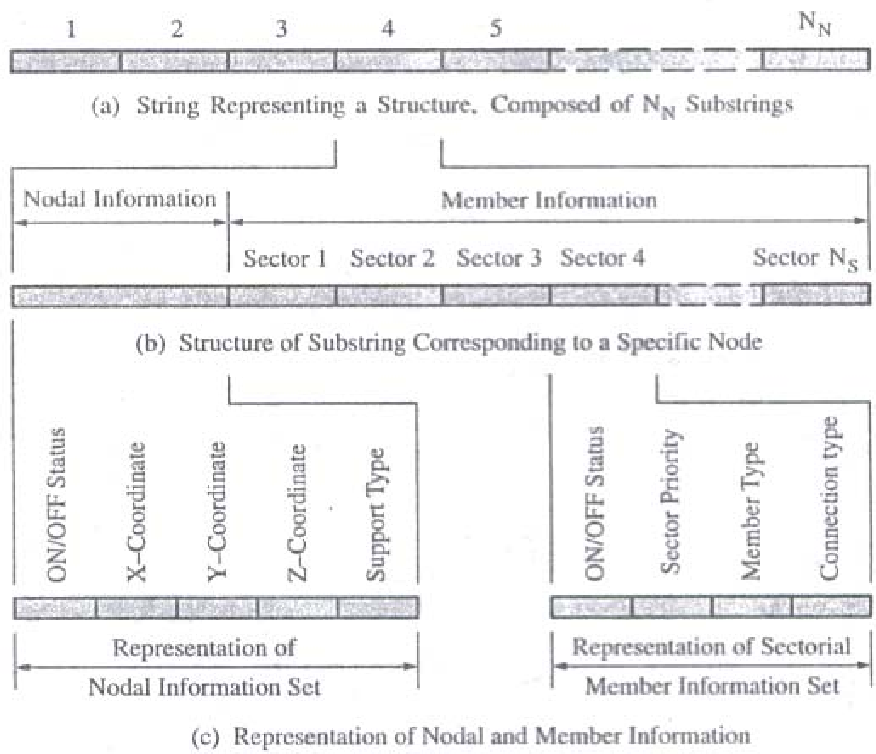


Figure (22) string representation scheme (**Shrestha and Ghaboussi (1998)**)

The optimum design is reached after 5400 and 9754 generations for both examples. The Weight-Generation relation and history of evolved shape during the genetic algorithm execution for the first example are shown in Figures (23 and 24)

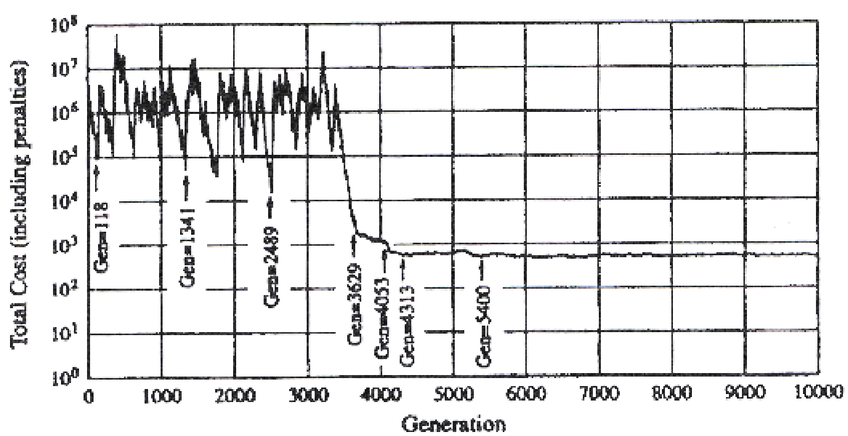


Figure (23) Weight-Generation cost profile of Example (1) (**Shrestha and Ghaboussi (1998)**)

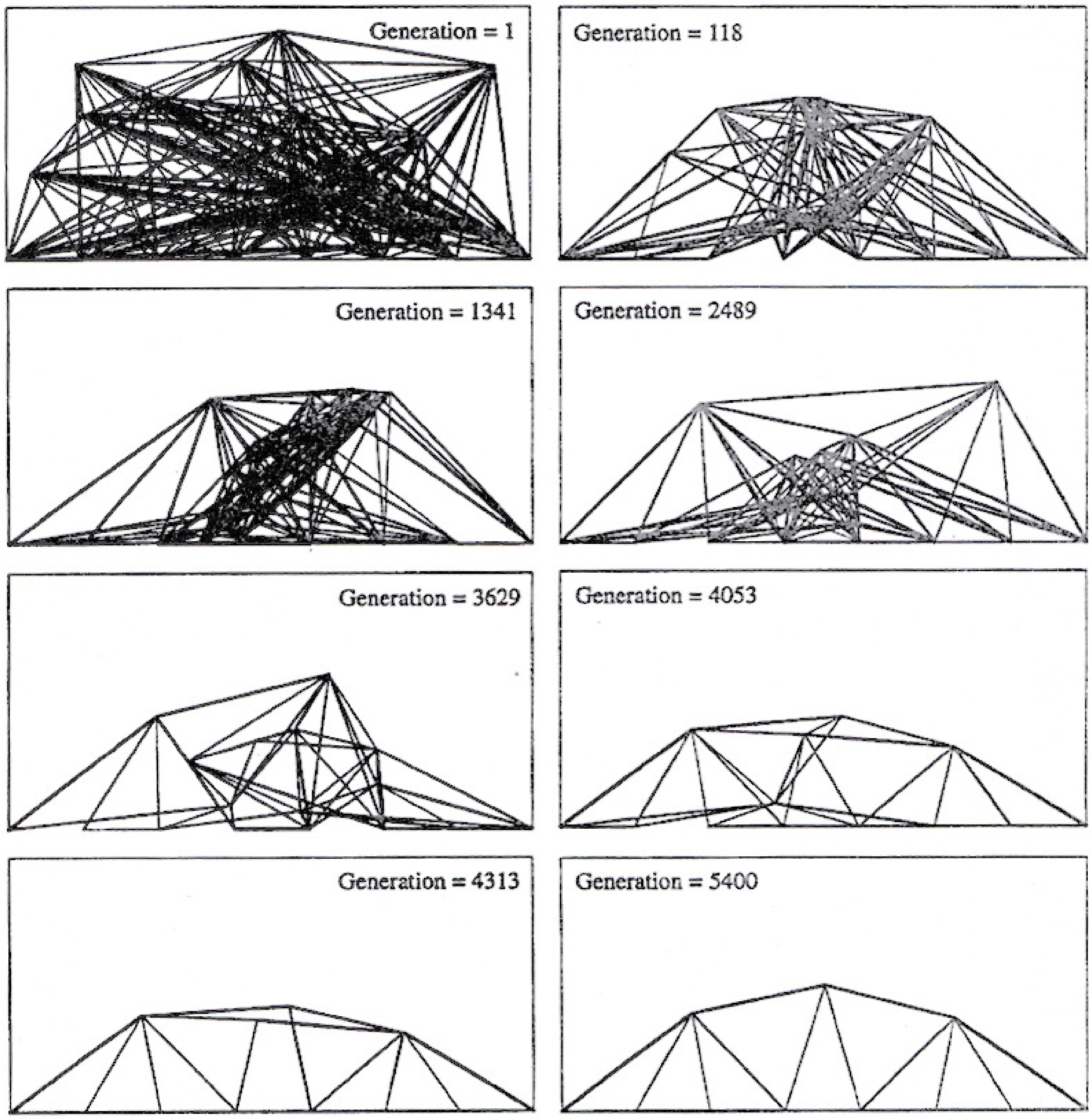


Figure (24) History of Evolver Shapes of Example (1) (**Shrestha and Ghaboussi (1998)**)

A fuzzy augmented lagrangian GA has been presented for optimization of steel structures subjected to the constraints of the AISC allowable stress design specifications taking into account the fuzziness in the constraints (**Sarma and Adeli (2000))**. The membership function for the fuzzy domain is found by the intersection of the fuzzy membership function for the objective function and the constraints using the max-min procedure of bellman and zadeh. Nonlinear quadratic fuzzy membership functions are used for objective function and constraints. One of the objectives in the work is to model the effects of imprecision, uncertainty, or fuzziness in addition to improving the convergence and efficiency through the use of fuzzy set theory in the formulation of a GA-based structural design optimization problem.

The algorithm was applied to optimum design of two space axial-load structures. The first is a 72-member space truss subjected to two loading conditions for which the optimum solution obtained by the simple and the fuzzy Gas are 1.6564kN (372.40 lbs) and 1.6208 KN (364.40 lbs) in 2,776 and 1,758 generations, respectively. The second is a large 37-story structure with 1.310 members, 332 nodes and 105 groups of members steel space truss as shown in Figure (25). For that example, minimum weight of 4,093.0 kN (920.2kips) s been obtained using the simple augmented lagrangian GA after 2,639 iterations using 400 populations of design variables as shown in Figure (26).

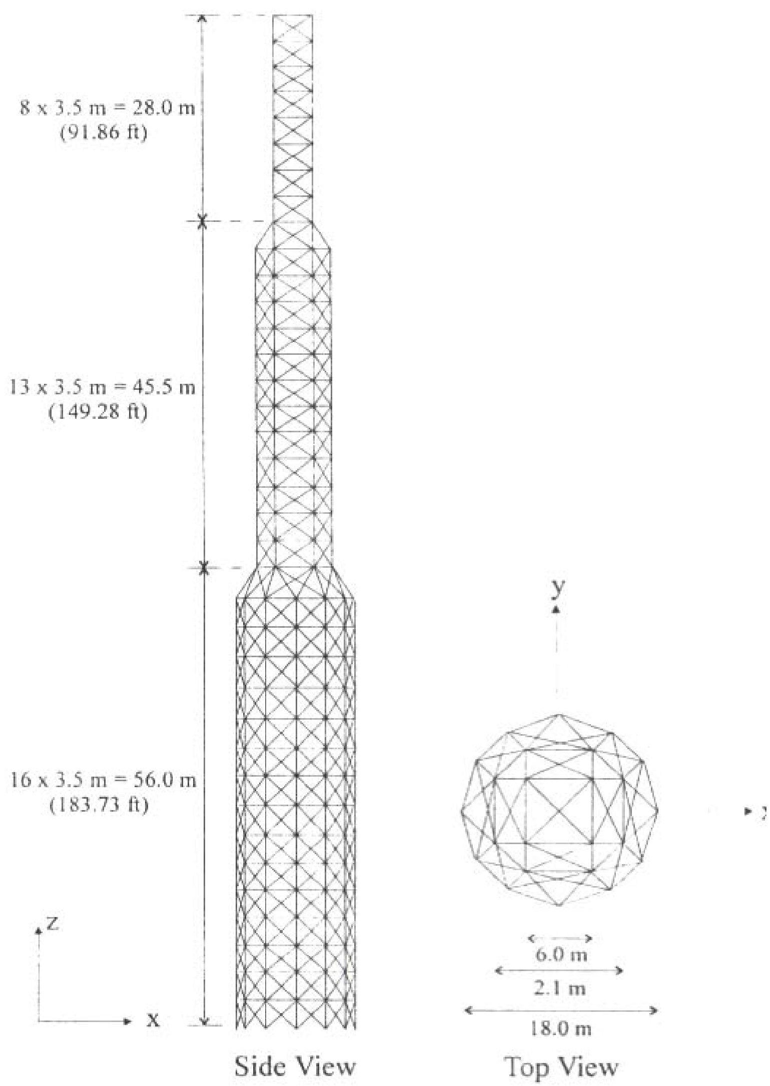


*Figure (25) 1310-Member Steel Space Truss (***Sarma and Adeli (2000)***)*

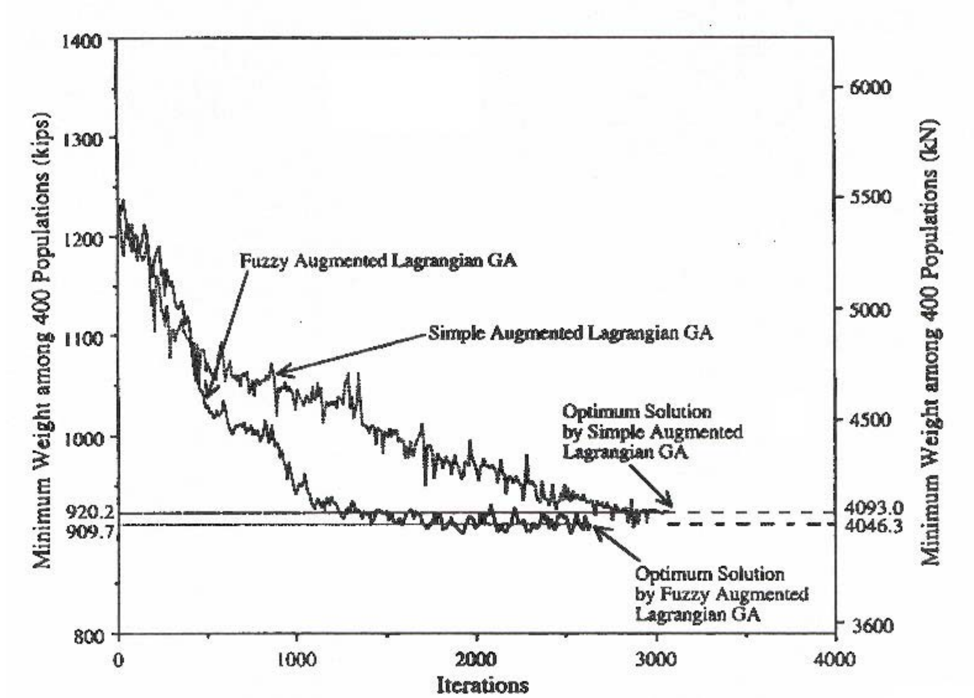


Figure (26) Design histories for simple and fuzzy GAs for optimization of 1,310-member steel space truss (**Sarma and Adeli (2000))**.

Jenkins (1997) developed adaptations to the standard Genetic algorithm by the development of a space condensation heuristic which progressively reduces the size of the multidimensional space being searched leading to more economic application. Adaptations include controls and the type of penalty function used for design constraints. The enhancement of procedure control has been carried out by using heuristics to update the parameter value selections (PSELS) during the application of the algorithm generation after generation. By assigning weights to design variables that lead to the highly and poorly fit objective function (+1 for highly fit and -1 for poorly fit), and as the processing continues, the record is expected to indicate any trends in selection. Another adaptation was carried out in the application of penalty function which was suggested to relate the value of penalty function to the extent of constraint violation in the form:

$$P = k(d)^m$$

Where

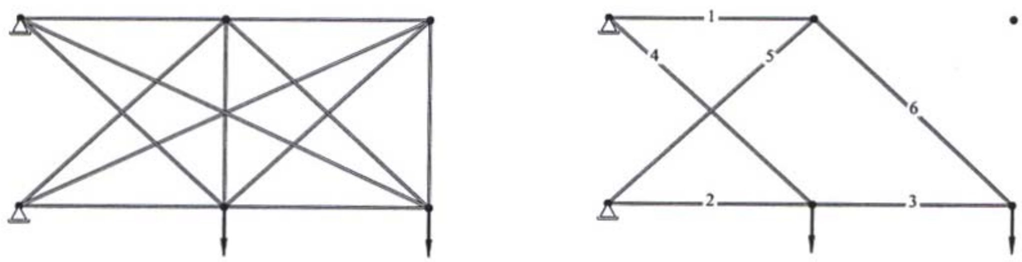
d	= q/a	for q>a
d	= a/q	for a>q
a	is the value of constraint	
q	is the allowable value of constraint	
k, m	are justification problem dependent factors	

The adapted procedure was applied to the design of multistory space frame for minimum volume under the BS5950 design constraints. Population size of 50 and maximum number of generations of 100 are used to perform 10 different analysis using the standard and the suggested adaptive technique. More optimal volumes are obtained when applying the adaptive technique indicating the importance of space condensation heuristics in improving the processing time needed. On the other hands, less importance has been assigned to the adaptivity of controls and the constrained handling strategy.

Genetic algorithms were presented and applied to real-world truss examples with discrete practical sections available in market by **Galante (1996).** To cope with practical considerations, minimization of the number of cross section types is applied as an optimization criterion in addition to the minimization of the truss weight. Shape optimization is also considered in the developed GA which applies the two point crossover to binary coded chromosomes. The constraint related to the elastic and plastic buckling is also applied in addition to stress and displacement limits. The genetic algorithm proposed was applied to the optimization of the traditional 10 bar truss shown in Figure (3) and another 160 bar transmission tower. For the 10 bar truss example, different situations are considered concerning the consideration of buckling constraint, minimization of the number of cross sections, and the shape optimization. As compared to previous studies (**Goldberg and Santani (1986)**, **Rajeev and Krishnamoorthy (1992)**) and others), the suggested procedure proposed less weight in case of the same constraints and objectives for both examples.

A comparison between the genetic algorithm evolution strategy simulation and random cost method was applied to the topology optimization of trusses by **Baumann and Kosty (1999)**. Random cost turns out to be an optimization method with attractive features. In comparison to the genetic algorithm approach previously defined, random cost turns out to be simpler and more efficient. Furthermore it is found that in contrast to evolution strategy, the random cost strategy's ability to find optima is independent of the initial structure which is related to the important capacity of escaping from local optima. The structural total weight was considered as the single objective (cost function) to allow for comparison. Two different truss optimization problems previously analyzed were investigated. The first problem is a well-known test case in structural topology optimization of trusses. It consists of six joints, two fixed supports and two loads acting simultaneously. The initial structure and the expected well-known optimal topology known are shown in Figure (27). Both methods, the GA-method and the RC-method, find this solution. In spite that authors reported that the genetic algorithm procedure was not able to find the global optimum directly for the second problem, it was reported that when using completely connected initial structure, global optimum can be obtained.

Examples previously discussed by **Galante (1996)** and **Rajeev and Krishnamoorthy (1992),** and others are again optimized by **Turkkan (2003)**. A floating point genetic algorithm proposed for optimizing structural systems with discrete design variables was applied to them. The new concept proved to converge to a better solution when compared to the binary coded genetic algorithms of the mentioned studies. Tournament selection is applied to the genetic algorithm developed in C++ language with whole linear crossover and non uniform mutation. The proposed GA was applied to the solution of the traditional 10 bar plane truss shown in Figure (4) and solved in the previous studies (**Galante (1996)**, **Rajeev and Krishnamoorthy (1992)**). As indicated in the results, modifications made on the standard genetic algorithm procedure lead to the global minimum without the violation of displacement and stress constraints. Real coded probabilistic model building genetic algorithm (PMBGA) was investigated by **Hiroyasu et al (2002)** and applied to the design of steel trusses.



Initial Structure Final (Optimized) Structure

*Figure (27) The Topology Optimization Truss Example (***Baumann and Kosty (1999)***)*

andgren and Cameron (2002) considered the application of genetic algorithm to optimal structural design under the presence of variation in loading, geometry and material properties. A Monte Carlo simulation was embedded in a genetic optimization algorithm to produce an output distribution for the objective function and constraint functions at each design evaluation. A hybrid genetic/non-linear-programming algorithm was used with a multi-objective formulation to locate a design that is optimal under the primary design criteria, but is simultaneously insensitive to variation. Cross-sectional, geometric and topological design changes are considered for which weight minimization subject to maximum stress constraints were considered. Specific examples presented include the famous ten bars truss structure and structural inner panel for an automotive. Three advantages were reported for the incorporated method. First, the design process accounts for realistic parameter variations so the design is practical rather than a mathematical abstraction that is of little use in the real world. Second, the design generated is less sensitive to variation in loading, restraints and material properties and is therefore less likely to fail in practice. Finally, the procedure can accelerate the global search to locate potentially good regions in the overall design space. The increase in computational effort is significant, but the results are superior to conventional approaches.

In an attempt to facilitate easy applications for structural optimization using the genetic algorithm as optimizer, a genetic algorithm (GA) based Finite element analysis (FEA) procedure was developed (**Ali et al (2003)**) for size and shape optimization of planar and space trusses. Topology optimization did not been included in the proposed procedure. The purposed procedure interfaces a binary GA within a FEA software package in order to initially test the applicability and viability of such integration. Cross-sectional area can be either continuous or predefined discrete. Pre-defined discrete cross-sectional areas, their properties, constraints and design checks were taken from the American Institute of Steel Construction. Serviceability and fatigue constraints did not been included in the procedure. In addition, special features of the GA was included to dynamically alter the population size, and the crossover and mutation rate in order to facilitate faster convergence and hence reduce the computational effort required. Weight was specified as the objective function to represent cost, constraints were handled by the adaptive penalty method in which the GA adapted itself as search and optimization process progressed. The paper also brings a focus on the applicability of integrating a GA as an optimization tool within FEA software. The genetic algorithm was developed in MATLAB and the finite element code used is the commercial ANSYS program with text file interface. It was shown by way of many examples solved by numerous mathematical, as well as other heuristic approaches in the literature that the purposed methodology was reported to be quite efficient and capable of finding lighter and reasonable structural designs than that reported in the literature. Moreover, it is shown that the purposed method removes the immense effort required in coding ones own finite element codes by utilizing already existing finite element software. Nonetheless, it was found that even with a GA, optimization for very large problems was computationally extensive such that for the largest optimization model presented in the paper (i.e. the 47 bar truss planar tower) consumed as much as 14 h—on a Pentium III processor to optimize, where convergence was achieved within 100 generations. This was primarily due to the large number of design variables involved for this particular structure.

Coello et al (1996) applied genetic algorithm for design of axially loaded non-prismatic columns. Cross sectional shape was considered as the main design variable and minimum weight was used as the objective junction subjected to buckling and strength constraints. Fine tuning of the GA procedure were carried out to suit real representation and utilizing a fitness history from which selection of best solution can be retrieved as follows.

- A certain value for the random number seed was chosen and made constant
- Constants for the population size and the maximum number of generations was chosen (400 chromosomes and 50 generations, respectively)
- Loop the mutation and crossover rates from 0.1 to 0.9 at increments of 0.1 was performed (this is actually a nested loop which implied that 81 runs were necessary).
- For each run, 2 files were updated. One contained only the final costs, and the other has a summary that includes, besides the cost, the corresponding values of the design parameters and the mutation and crossover rates used. When the whole process ended, the file with the costs is sorted in ascending order, and the smallest value is searched for in the other file, returning the corresponding design parameters as the final answer.

As design variables are continuous, jolting point representation was reported as the best solution compared with binary representation. Such representation led to more precision and better speed since chromosomes can be of considerable shorter length. The technique was succeeded to reduce the volume of steel columns up by 30% with respect to more traditional techniques.

3.3. Design of Concrete Structures

Rafiq and Southcombe(1998) introduced an approach to optimal design and detailing of reinforced concrete bi-axial columns using genetic algorithms. Optimal bar size and bar detailing are the used design variables of the suggested search. The procedure attempts to keep the sectional moment capacity and cross section and obtain the minimum reinforcement area leading to more economical design. The British standard (BS8110) was followed concerning the capacity calculation and reinforcement arrangement. A declarative approach was used to check the exact bending capacities of the section about both axis of the column. Binary coded GA was developed in which the chromosome lengths are dynamically selected for each particular design related to the column dimensions. Maximizing the Only 50 generations with population size 50 was reported to lead to the optimum solution. Compared to the code design, genetic algorithm leads to optimum or very close to optimum bar arrangements

Coello et al (1997) presented a genetic algorithm optimization model for the design of rectangular reinforced concrete beams subject to a specified set of constraints. The model considered the minimization of the cost of the beam considering the costs of concrete, steel and shuttering leading to practical design. Simple genetic algorithm was applied and results were compared to those obtained via geometric programming. Strength design procedure was adopted for which the ultimate concrete strain is 0.003 and trapezoidal stress distribution was assumed. The same procedure adjusted for tuning of genetic algorithm procedure suggested by **Coello et al (1996)** was customized. **Matou et al (2000)** selected the design of reinforced concrete beam among selected engineering problems and verified the efficiency of genetic algorithm in engineering optimization problems.

The optimization of construction costs of mass concrete structures such as dams, foundation slabs, and bridge decks was carried out by **Fairbairn et al (2004).** The proposed model used the genetic algorithm in selecting the material type, placing temperature, height of lifts and time interval between lifts as design variables. These variables control the cost of mass concrete structures which was used as the objective function. Coupled thermo-chemo-mechanical model was incorporated into a 3-d finite element code to simulate the hydration process while genetic algorithm was customized for optimization. Binary coded representation was performed with single point crossover and tournament selection together with elitism. As an illustrative example, the proposed model was applied to a concrete dam for small hydropower plant. The procedure proved to be applicable to actual design of massive structures in which early age cracking is a predominant design constraint.

A systematic approach to the reliability analysis of precast concrete structures, using Genetic Algorithms, was presented by **Catallo, L. (2004)**. The problem is considered as an anti-optimization problem which is mathematically defined by simultaneous search for the highest and the lowest value, and, as previously said, for the difference between them. The engineering definition of the anti-optimization procedure can be summarized as the process to develop the best solution having in mind the worst. The problem was formulated in terms of safety factors and the membership function, over the failure interval, is searched for several defined Limit States. Due to unavoidable uncertainties, and knowing that the geometrical and the mechanical properties that define the structural problem cannot be considered as deterministic quantities, such uncertainties were modeled using a fuzzy theory based approach. For simplicity, uncertainties due to restraints did not been considered in the study. For the prestressed frame case studied, the variables which influence more the structural response are the steel strength in the pillars, the prestressing steel strength and the live load in post-tensioned RC continuous beam and the prestressing force. Roulette wheel selection scheme was employed to the FORTRAN developed genetic algorithm proposed with probability of crossover and mutation of 80 and 1 percent, respectively. For each level of uncertainty, the reliability problem is seen as an anti-optimization problem, where the worst unsafe solutions are achieved using genetic algorithms.

Peng and airfield (1999) presented an integrated design optimization combining the mechanism method with genetic algorithms for the optimization and design of arch bridges. The method proposed utilizes the combination of the mechanism method which is one of the principal arch assessment tools and the genetic algorithms which are powerful numerical function optimization techniques. The mechanism method, which is a limit state plastic analysis which supposes a four, or five hinged mechanism for the arch's collapse mode was incorporated in a simple computer program called (Archmech) for arch analysis. The method was proposed as a design aid for structural engineers involved in the assessment, maintenance and repair of existing bridges, or the design of new arches. Three objective functions was considered representing minimizing the ratio between the 1/4 span thickness (t) and the crown rise h_c (τ), minimizing the total cross sectional area (*A*), and maximizing the ultimate load (*P*). Design variables were considered (α, β, δ) can be defined as (Figure (28)):

α = h_q/h_c is the $\frac{1}{4}$-span to mid-span depth ratio

β = h_0/h_c is the backfill to mid-span depth ratio

δ = h_c/s is the mid–span depth to span ratio

Trials showing results from Teston Bridge, Kent and a range of other sample optimal arch designs were presented with associated algorithm efficiency data. The combination of the mechanism method with genetic algorithms were reported to prove successful in the quest for an optimal arch bridge design with additional usefulness for engineers involved in routine bridge assessment and maintenance. Groups of equally feasible designs, all close to the optimum solution, were produced. The optimization procedures used proved computationally efficient: they all ran quickly on low specification personal computers.

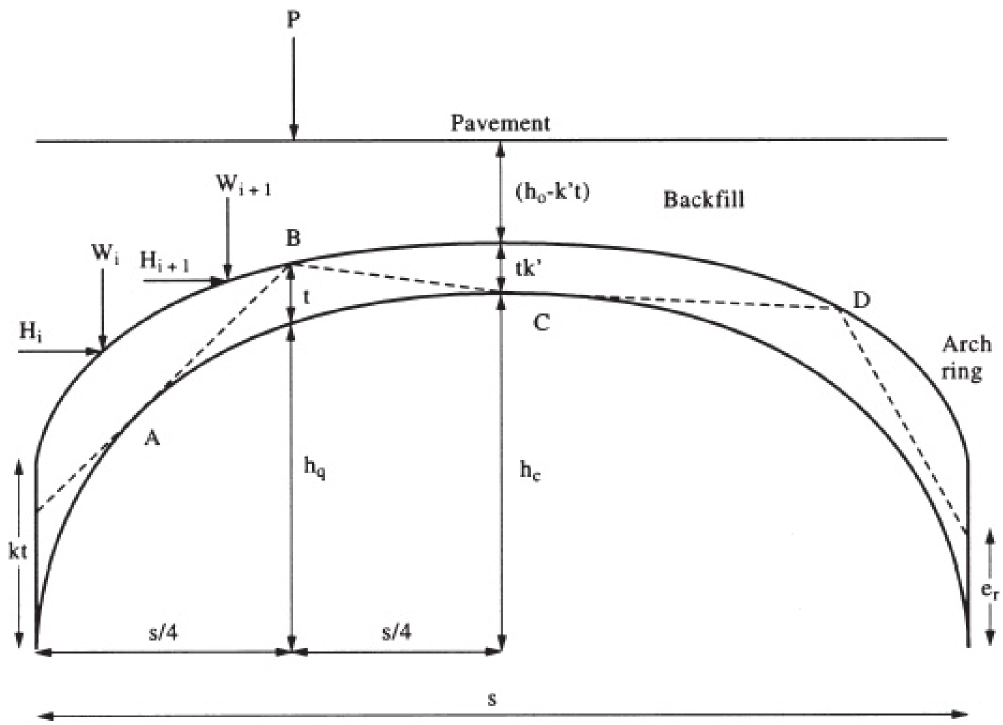


Figure (28) Configuration of Arch Bridge (**Peng and airfield (1999)**)

3.4. Structural Systems and Models

Wang and Chen (1996) used the genetic algorithm approach to optimize the location of supports of beams for maximum fundamental eignvalue. Three boundary conditions are considered for which the location of three supports is optimized. Rayleigh-Ritz method for beam vibration analysis is used to evaluate the eign values which constitute the fitness function without any scaling. A 30 digit binary string is used to encode the problem representing each support by 10 bits allowing 1024 different location of each support. 30 generations with population 30 individual each are use to make about billion (10^9) of support combinations.

Miles et al (2001) have introduced a system BGRID for the conceptual design of multi-story office buildings. Conceptual design, as reported, includes grid dimensions, structure-services integration strategy, Environmental strategy, fire escape rules, spaces required for heating and mechanical plant, and clear floor to ceiling height. The suggested layout is based, beside the structural considerations, on lighting requirements, ventilation strategies, limitations introduced by available building materials, and available structural systems. The determination of such components of conceptual design reflects the majority of costs of project construction (about 80 percent (**Miles et al (2001)**). The system has a user friendly interface to be used as a decision support system (DSS) by architects; building services engineer, or even clients rather than structural engineers.

Real number coded representation is selected to encode the design variables into the genotype chromosome which includes variable number of genes (digits) according to plan dimensions. The main design variables represented in the genotype are the coordinates of each column (x and y), structural-service integration strategy (separate, partially or fully integrated), environmental strategy (natural ventilation, mechanical ventilation or air conditioning) and clear floor to ceiling height. Separate parts of the genotype are assigned for the x-coordinates of columns, y-coordinates of columns and other factors to produce the three parts genotype illustrated in Figure (29), which represents six columns floor. The first six cells of the chromosome represent the x-coordinate of columns and digits 6 to 12 represent the y-coordinates. The remaining three genes correspond to separate structural service, mechanical ventilation, and floor height 2.9 m, respectively.

0	25	50	75	90	100	0	20	40	65	80	90	0	1	2.9

Figure (29) Genotype used in **Miles et al (2001)**

Crossover operator is applied separately for each part of the chromosome string shown using single point crossover with random location and mutation is performed with probability of 1 percent. Fitness function of the problem includes the constraints which are divided into hard and soft constraints. Hard constraints as the floor height limit, design option structural system compatibility, and uniformity of grid are considered through the use of penalty functions. The objectives of optimization are weighed by the user to emphasize the relative importance of each objective among others. The three objectives to be weighed are summarized as the large clear span, the minimum cost, and the minimum environmental damage. Costs are estimated using some features as the total weight per floor area, overall building height, and net/gross floor area ratio rather than exact costs. Structural design of floor beams is estimated according to span/depth ratios obtained from manufacturer's catalog. The system is reported to have good user interaction and smart behavior with the deficiency of requiring more presentation of design summary and graphical form of presentation.

Methods based on genetic algorithms optimization were derived for mesh partitioning problem for explicit parallel dynamic finite elements. (**Sziveri et al (2000), Papadrakakis et al (2003)**) and dynamic tuning of structures, which eliminates the vibrations by altering the dynamic properties of the system (**Tesar and Drzik (1995)**). The relationship between damping and vibration amplitude was obtained by **Li et al (2000)** Based on full scale measurements of damping in a tall building using a time series analysis method (TSA). Two models of damping in a tall building, the artificial neural network (ANN) model and the auto-regressive (AR) model, were established by employing ANN and AR methods, and used to predict the damping values at high amplitude level, which are difficult to obtain from field measurements. In order to get high accuracy, a genetic algorithm strategy was employed to aid in training the ANN. Comparison analysis of the neural network model and the AR model of damping is made, and the results are presented and discussed. The results predicted by the AR model and GRNN model of damping indicated that the two types of models have given satisfactory results. The maximum absolute error caused by the AR model and the GRNN with GA is 0.061 and 0.046 in the direction 1, respectively, and the corresponding maximum relative error is 10.6% and 9.8%, respectively. In the direction 2, the maximum absolute error caused by the AR model and the GRNN with GA is 0.058 and 0.028, respectively, and the corresponding maximum relative error is 10.3% and 5%, respective. It was also concluded that the prediction curves produced by the GRNN with GA are a little closer to the actual curve than that given by the AR model in the direction 1 and direction 2. Comparing the prediction errors and curves of the AR model and the GRNN with GA resulted in the conclusion that the performance of the neural network model is better than that of the AR model in the direction 1 and direction 2 under the experimental conditions reported.

Detecting the extent of damage in structure from modal data (natural frequencies and mode shapes) can be viewed as an optimization problem. Using modal based methods in practical applications reduces time and costs of performing damage monitoring and predictive maintenance. Such methods are based on the fact that damage of structural members alters the stiffness of the structure and consequently modal properties. The minimization of some error functions derived from the difference between measured and suggested values of dynamic properties is the aim of such analysis (**Shtovba and Pankevich (2004)**).

Genetic algorithm has been applied to eign-sensitivity analysis of damage in structures by **Friswell et al (1998)**. The objective of the study was to identify the position of one or more damage sites in a structure and to estimate the extent of damage at these sites. Design variables include discrete values of damage location and continuous variable indicating the extent of damage as a percentage reduction in stiffness. The optimization The objective function used is based on the measured data ad consists of three terms related to the error in natural frequencies, and the error in mode shapes and a term to weight against two damage sites. Genetic algorithm used single point crossover with population of 10 members per generation, crossover probability 60 percent and mutation probability of 0.5 percent. A simulated cantilever steel beam is tested for which the change of only 5 natural frequencies is considered to locate damage. Four cases of damage is applied to such beam including the damage of single site and the damage of conflicting element near the edge, the damage of two sites and the case of adding extra mass at the end including systematic errors. The proposed method estimates well the location of damage in the simulated cantilever beam example. Another experimental example of cantilever plate with saw cuts has been also presented for which the correct location of damage was found after only 8 generations.

Rao et al (2004) have proposed a method for locating and quantifying the damage in structural members using the concept of residual forces. Genetic algorithm has been applied for the minimization of objective function consisting of the sum squared diagonal terms of the residual force matrix. All modes of vibration are considered in the formulation. A computer program in C language is developed to perform the analysis using Binary coded genetic algorithm. Two point crossover and Tournament selection approach are applied in the genetic algorithm with population 40 individuals. The crossover probability is taken 100 percent while the mutation probability of 0.1 percent is considered. Te proposed procedure has been applied to several problems with different damage extents to test the applied methodology. The first is a plane truss having reduction in the stiffness of two members with different extents. The second is a cantilever beam with 10 elements for which cases if undamaged structure, beam with two elements damaged, and beam with element failed (100% reduction in stiffness). Portal frame example with 6 elements has been also discussed. The solution using genetic algorithms results in excellent agreement with that of theoretical predicted mechanical simulation.

3.5. Optimization of Composite Structures and Composites

In their review of methods used to optimize composite panels, **Venkataraman and Haftka (1999)** reported that genetic algorithms have been the most popular method for overcoming the optimization complexity of composite panels. This can be attributed to the fact that the problem is discrete in nature such that the ply orientation must be one of specific values produced by the manufacturer. Optimum design of the weaving structure of three-dimensional (3-D) reinforced composites was carried out (**Okumura et al (1995)**) and the stacking sequence of composite laminates was investigated (**Lin and Lee (2004)**)

A formulation and solution technique using genetic algorithms (GA) for design optimization of composite leaf springs was presented by **Rajendran and Vijayarangan (2001)**. Leaf springs are commonly used in the suspension system of automobiles and are subjected to millions of varying stress cycles leading to fatigue failure. For optimal weight with adequate strength and stiffness, design variables were leaf thickness and width. It was observed from the study that optimization using GA leads to larger weight reduction due to its search for global optimum as against the local optimum in traditional search methods.

Description of the concept of using genetic algorithms (GA) procedures in layout optimization of composite structures was presented (**Muc and Gurba (2001)**). The layout optimization was understood in the sense of stacking sequence, shape and size (material, volume) optimization. The attention was focused on the applicability of genetic algorithms in conjunction with the finite element computation of objective functions. Main conclusions of the study contains that proper coding of design variables and then selection of a new population are essential for optimization and that optimization procedures do not require any sensitivities studies what seems to be a great advantage over the classical optimization methods.

Soremekun et al (2001) explored several generalized elitist procedures for the design of composite laminates. The problem design variables are discrete as ply angles and ply thickness can only be available in manufacturer specific values. Maximizing the buckling load of simply supported composite plate and maximizing the twisting displacement of cantilever composite plate was set as the two objectives of the analysis. Generalized elitist genetic algorithm (GEGA) was suggested as an alternative to the standard genetic algorithm (SGA). It is shown that the generalized elitist selection (GES) procedures are superior to the single individual (SI) procedure for two types of problems. The first type involves many global optima, and the GES procedure can find several global optima more efficiently than the SI procedure and this may give the designer more design freedom. The second type of problem involves an isolated optimum surrounded by many designs with performance that is very close to optimal. It is shown that GES procedures can find the optimum and near optimal designs much more easily and reliably than the SI procedure.

A methods for composite laminate optimization based on genetic algorithms was investigated by **Grosset et al (2002)**. The work investigated how the efficiency of standard genetic algorithms can be improved by adding some statistical (the bayesian Optimization algorithm BOA) processing. Simple optimizations of the in plane properties of a laminated plate were used in this preliminary investigation. Only linear case were considered to maximize the in-plane longitudinal stiffness A_{11} subjected to constraints on the transverse stiffness A_{22} and shear stiffness A_{66} of a symmetric and balanced composite laminate. The problem constitutes discrete parameter problem as ply angles can take only set of values (15^o, 30^o, 45^o, etc….). Since BOA-GA model is a faithful representation of the actual structure of the data, it can achieve better results than the conventional recombination and selection operators of the standard GA, which rely for a large part on chance. For the non-linear case, however, it is somewhat surprising that the linear models keep up with the standard GA. Very encouraging results were included in the study which show that there is room for improvement on standard GAs.

Hansel et al (2002) presented realizing the weight-minimal laminate structures by topology optimization using the genetic algorithm and heuristic optimization algorithm. two alternative approaches for. Topology optimization was carried out in a layer-wise manner such that the individual laminate plies are allowed to have their individual topologies. In addition to sizing (adaptation of lay up angles and single ply thicknesses) and shape (the optimization by the variation of the outer shape of the considered laminate structure) optimization, the techniques of topology optimization have the potential to reveal significant weight savings by adapting the laminate connectivity to the given requirements. Low-cost manufacturing was ensured by limiting the choice of orientation angles to 0, 45, and 90 and fixing the ply thicknesses to the discrete values 0 (no material) and h (whole ply material). The importance of such optimization comes from the fact that the use of laminates with unidirectional carbon fiber reinforced plastics (CFRP) plies is well established for lightweight constructions, in particular in aircraft and spacecraft engineering. The required structural analyses are made by means of commercial finite element codes (ANSYS and MSC/ NASTRAN NASTRAN). The objective function was taken as the minimization of total mass while large number of discrete design variables and large number of constraints were contained. Design variables are considered as the material distribution and the local reinforcement directions to the given structural needs. Two examples of laminate structures show the effectiveness of the proposed algorithms. Binary coding of the plate topology was performed to demonstrate the existence of material or void as shown in Figure (30).

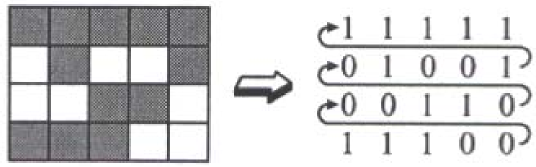


Figure (30) Coding of Plate Topology Phenotype (Distribution of Void/Material)
(**Hansel et al (2002)**)

For the example of cantilever plate for which the optimum topology is shown in Figure (31), the total weight of 3.25 g was reached which was reported to be about 15% less than the weight of the structure when solved using the heuristic optimization algorithm.

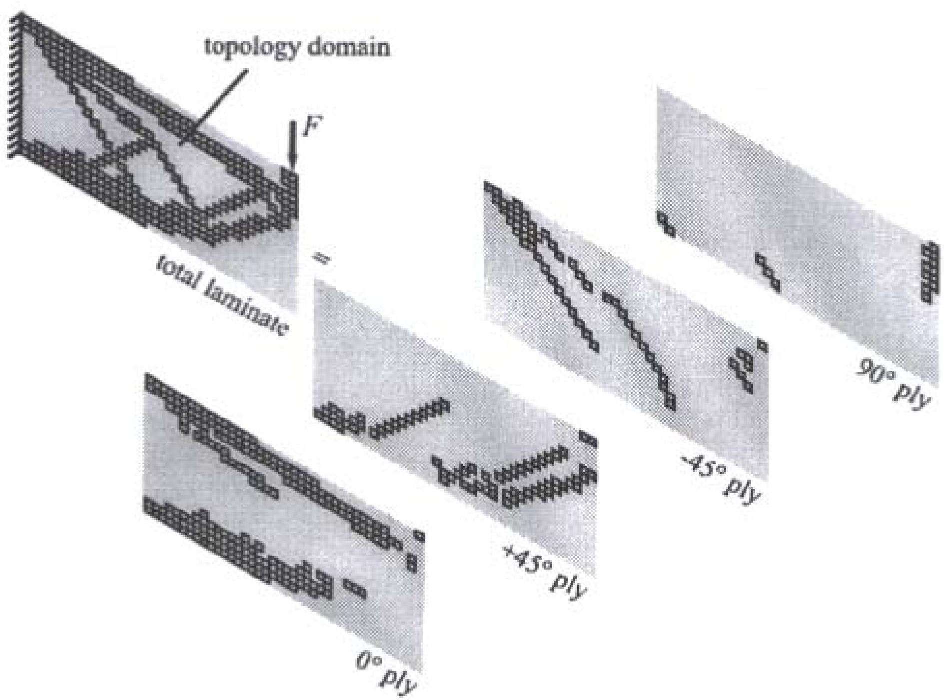


Figure (31) Optimized Cantilever Plate (**Hansel et al (2002)**)

For the aluminum cantilever plate shown in Figure (32), weight could be reduced from 13.5 g to only 10.8–11.4 g which constitutes a further weight reduction of about 15–20% over the heuristic optimization algorithm. The design of the L-shaped cantilever (Figure (33)) using genetic algorithm is also similar to the design found by the heuristic algorithm while The genetic algorithm requires about 3500 finite element analyses instead of about 50 analyses with the heuristic algorithm.

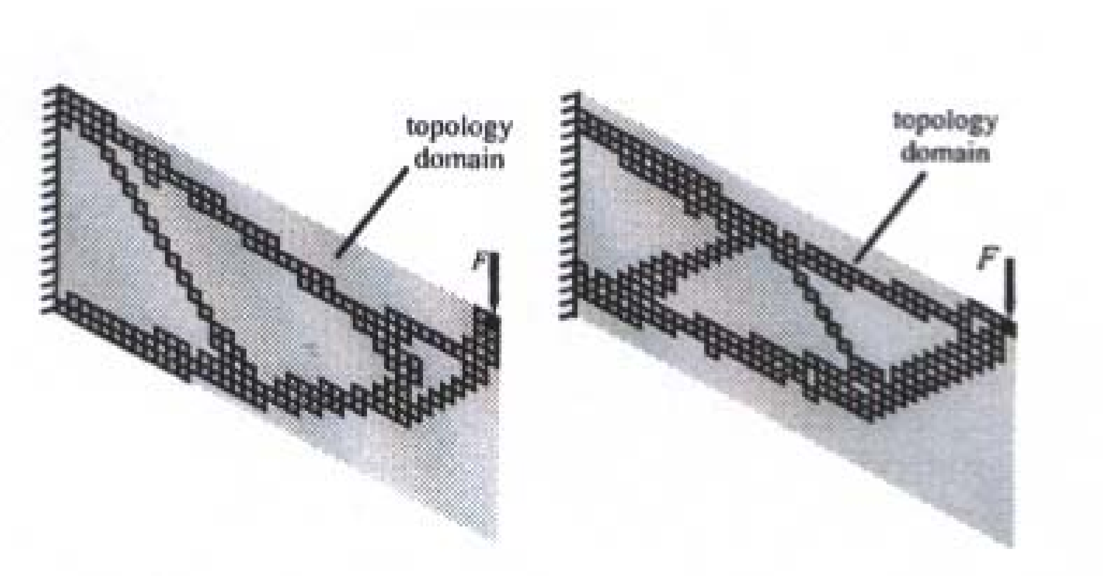


Figure (32) Optimized Aluminum Plate (**Hansel et al (2002)**)

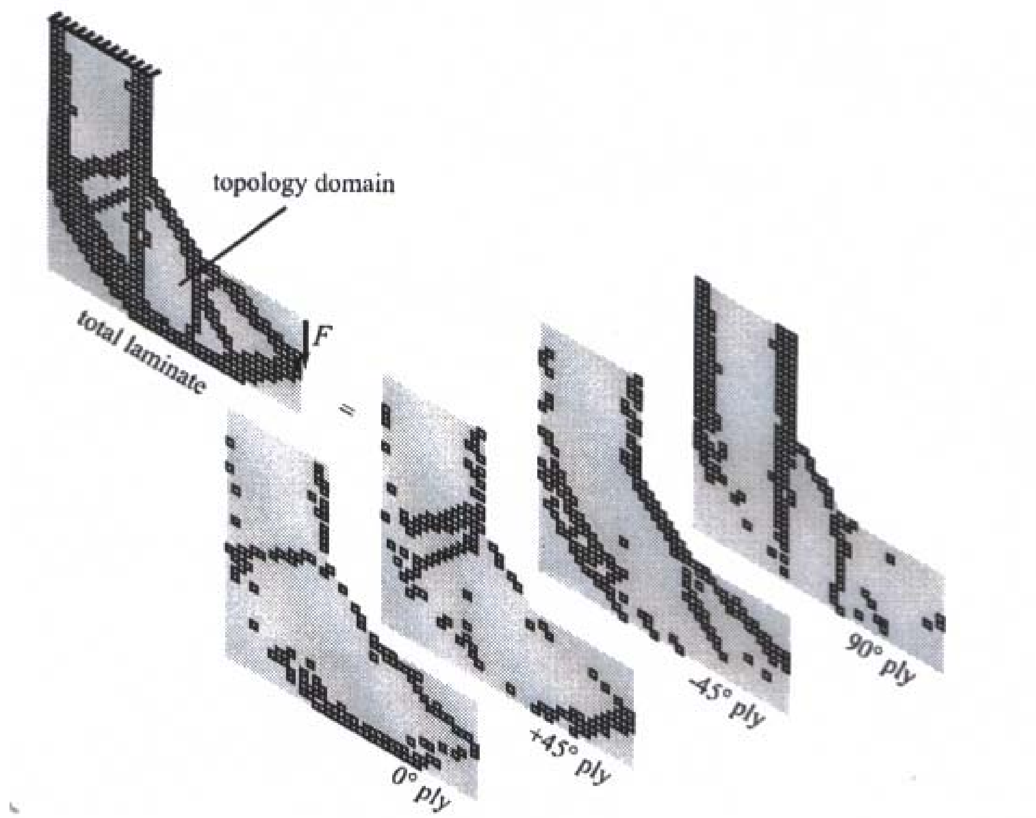


Figure (33) Optimization of L-Shaped Cantilever (**Hansel et al (2002)**)

Finally, to illustrate the efficiency of composite structure, it was reported that the optimized aluminum structures have a weight of about 10.8–13.5 g while the structures of composite material have a weight of only 3.25–3.8 g.

The optimization of laminated and sandwich plates with respect to buckling load and thickness was performed by **Di Sciuva et al (2003)**, using different sets of constraints such as the fundamental frequency, the maximum deflection under transverse uniform distributed load, the mass and the buckling load. genetic algorithm and simulated annealing was used to solve the optimization problem together with two plate models (classical plate theory and cubic zig-zag model). The calculations reported in the study were aimed mainly to compare the two evolutionary algorithms (GA and SA) and the two plate theories (CLT and CZZ). The results of the performed investigations show that the evolutionary methods are simple to implement, and give good results in all the studied problems. The performed analyses show that the two evolutionary algorithms provide almost the same results though the SA procedure is less time consuming; furthermore, results of the two displacement theories are the closer to each other the higher the side-to-thickness ratio is.

3.6. Active and Passive Control

Structural control aimed at enhancing the structural functionality and safety against natural hazards as strong earthquakes and speed wind gusts by reducing the structural response. While passive control is attractive due to its simplicity, and as it is power free, active control is attractive due to its potential effects and large improvements of response (**Arfiadi and Hadi (2000)**). Passive control systems such as base isolation, viscoelatic dampers, and Tuned Mass Dampers (TMDs) have been implemented in a number of full scale buildings throughout the world (**Ahlawat and Ramaswamy (2003)**)

Optimal design of absorber system consisting of four TMDs to control the response of torsionally coupled structures to earthquake excitation using genetic algorithms is discussed by **Ahlawat and Ramaswamy (2003)**. Optimization aimed at controlling the torsional mode of vibration effectively in addition to flexural modes. The problem is categorized as multi-objective optimization problem including three objectives of minimizing (1) the maximum peak displacement, (2) the maximum peak acceleration, and (3) the maximum peak rotation. Several constraints were considered as the total mass of the TMD, maximum stiffness, maximum damping and maximum eccentricities. Constraints are implemented in coding of the chromosome for the GA as maximum and minimum limits. The building model shown in Figure (34) has been assumed to have the principle axis of resistance for all stories oriented along the x as y directions. The eccentricities of floors are different as the mass and resistance centers do not lie in vertical axis and the radius of gyration and translational to rotational stiffness ratio differ from floor to floor. Ground acceleration which is applied in an inclined direction is assumed the same at all points of foundations.

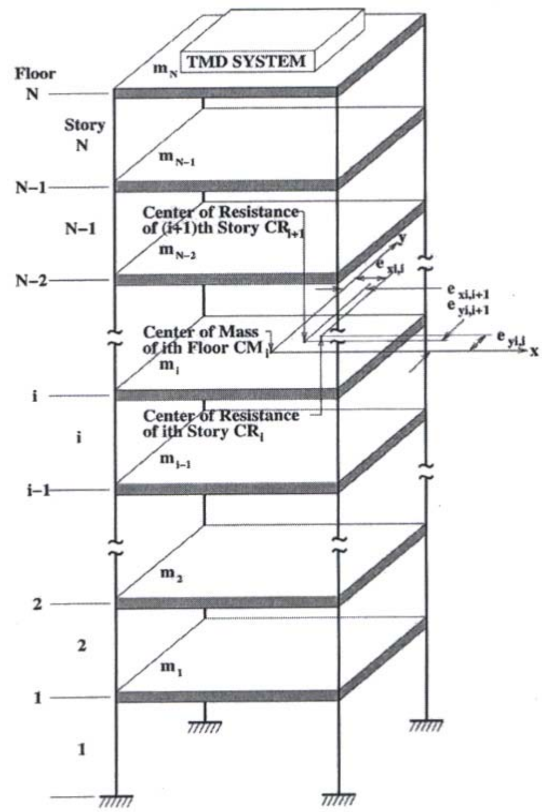


Figure (34) Idealized Torsionally Coupled Building (**Ahlawat and Ramaswamy (2003)**)

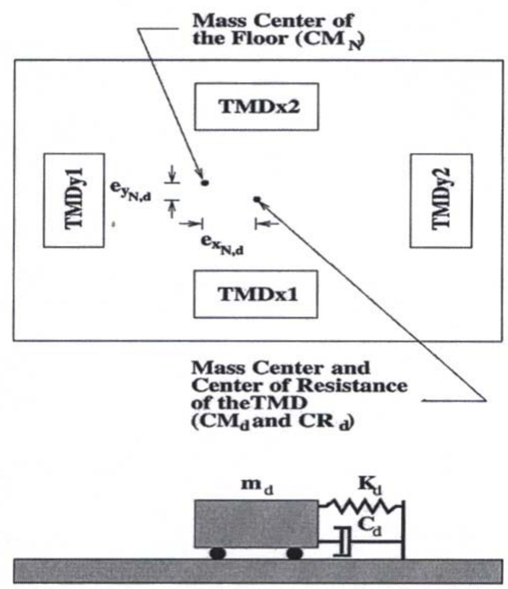


Figure (35) Suggested Arrangement on (TMD) on the last floor of Building (**Ahlawat and Ramaswamy (2003)**)

As a multiobjective problem having three objectives, three-branch tournament genetic algorithm was applied (Figure (36)). Binary coding was customized while crossover and mutation were performed at random locations. Another investigation was carried out for the optimal FLC driven hybrid mass damper (HMD) for torsionally coupled, seismically excited building by **Ahlawat and Ramaswamy (2003)**. As reported, the proposed control strategy proved to effectively control the torsional response in addition to the flexural response of the structure.

Park et al (2004) presented an approach for integrated optimum design of viscoelastically damped structural system. The use of viscoelastic dampers or larger amounts of structural members may decrease the probability of failure and the expected damage cost due to possible earthquake events although it may increase the initial construction cost. Thus, the life-cycle cost that mainly consists of the initial construction cost and the damage cost estimated by failure probability over its entire lifetime was introduced as the optimization criterion to be minimized. Considering the structure and dampers as a combined or an integrated system, the characteristics of the system and the design constraints can be accounted for from the design step.

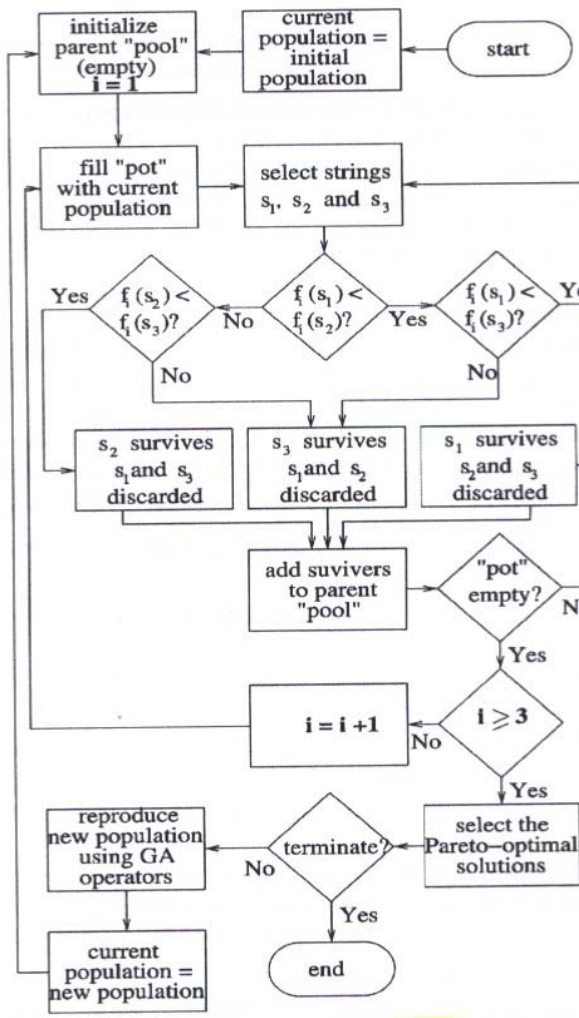


*Figure (36) Three branch tournament genetic algorithm (***Ahlawat and Ramaswamy (2003)***)*

Viscoelastically damped building was modeled, as shown in Figure (37), as a shear building structure having one degree-of-freedom (DOF) of horizontal direction per node (floor) which cannot express the effect of vertical displacement and/or rotational deformation in each node. Authors attributed the use of shear building model to the economic and simplicity consideration especially in the preliminary design stage which only needs basic information on the design variables. The frequency domain approach was implemented in the analysis as simple method is needed. Optimization problem was formulated by adopting structural sizing variables, locations and the amount of the viscoelastic damper as design variables. In practical applications, design variables such as column stiffness, damper capacity, and dampers locations may not be a continuous function because of commercial and manufacturing constraints. A genetic algorithm is used as a numerical searching technique in order to simultaneously find the optimum parameters of the integrated system. The story drift for defining the limit states of a building structure subjected to a horizontal ground motion was limited to values included in the UBC-97 provisions to control inelastic deformations and to prevent potential instabilities in both structural and nonstructural elements. The shear deformation limit of the damper was defined using the relative displacement of a viscoelastic material. In genetic algorithm application, population of 50 chromosomes as shown in Figure (38) was used with binary string size of 16n where n is the number of stories. Selection was based on roulette wheel selection, and crossover and mutation operations were performed with probability (p_c= 0.85 and p_m= 0.01). The proposed design method was verified with a numerical example of an eight-story building. From comparative results, it was found that the integrated design approach can improve the seismic performance of the structural system while it maintains low life-cycle cost. It was concluded that the proposed method has the advantages, not only from the viewpoint of seismic performance but also economic aspects.

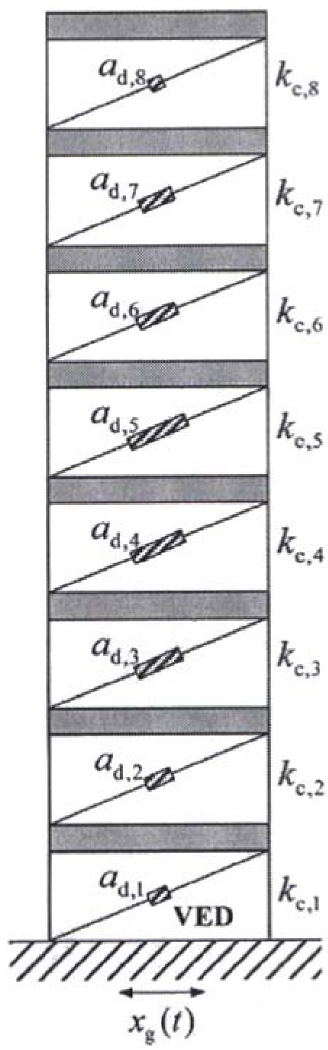


*Figure (37) Model of Controlled Building (***Park et al (2004)***)*

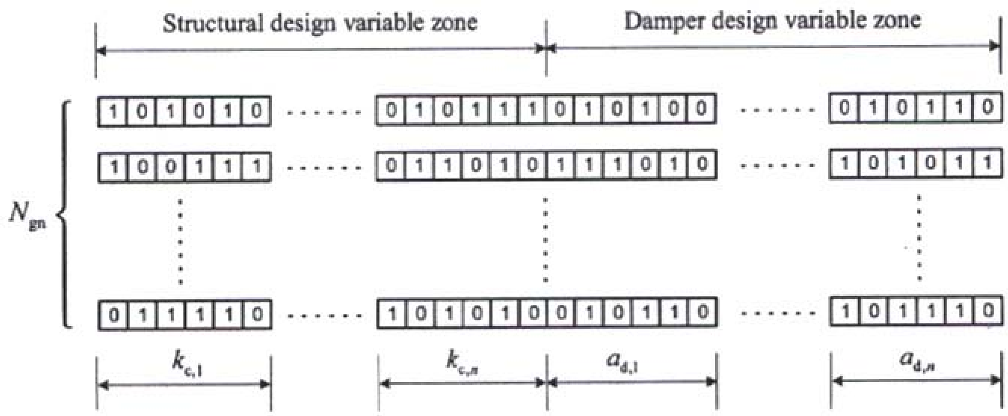


*Figure (38) Binary Code Representation (***Park et al (2004)***)*

Wongprasert and Symans (2004) applied the genetic algorithm to the optimization of damper distribution in controlling a 20 story benchmark building. Knowing the number of dampers and their properties, the target was to determine the distribution of dampers that gives the largest response reduction of the building. A genetic algorithm optimizer of the passive parameters of dampers and the controller gain was utilized for active and passive control of space structures (**Arfiadi and Hadi (2000)**). Devices included in the study are the mass damper and active bracing system for which static (direct) output feed back controller was utilized. Authors proposed the use of either binary coded or real coding genetic algorithm representation for design variables. Passive tuned mass damper (TMD), active TMD, and active bracing system are investigated examples introduced to verify the performance of the optimizer.

Too many investigations were carried out for the optimization of fuzzy logic control (FLC) in actively controlled structures (**Belari and Titel (2000)**). **Ahlawat and Ramaswamy (2002-a)** proposed a genetic algorithm based optimizer for fuzzy logic control (FLC) of hybrid control system composed of tuned mass damper (TMD) and active mass driver (AMD). Binary coded GA was used for this application with two-branch tournament selection for multi-objectives optimization with penalty function to account for constraints violation. Ten story shear building with HMD at top floor was used to demonstrate the multi-objective optimal design of FLC driven HMD. The stability of the FLC was examined for each of the Pareto-optimal design using the extreme (worst) initial conditions and was found to be stable. It was shown that, with the help of GA, the optimum values of design parameters of the hybrid control system can be determined without specifying the modes to be controlled. The proposed FLC driven HMD was found to be very effective for vibration control of seismically excited buildings in comparison with available results of the same examples but with a different optimal absorber.

Ahlawat and Ramaswamy (2004) proposed an approach for multi-objective optimal design of a fuzzy logic controller (FLC)-driven active tuned mass damper (ATMD) using genetic algorithm as an optimized. As genetic algorithms are more effective in handling a discontinuous and non-convex domain, a multi-objective optimization version of the genetic algorithm was proposed by for obtaining the FLC and ATMD design. The evaluation criteria for both the acceleration and displacement responses were used as the two objective functions for such multi-objective optimization problem. The stress limits were incorporated as constraints while the maximum number of sensors utilized in of control were limited to six. The two branch tournament approach was used to represent multi-objective criteria and penalty function was used for constraints violation in binary coded chromosome representation. The effectiveness and performance of the proposed FLC-driven ATMD has been investigated for the third-generation benchmark problem for the response control of wind-excited tall buildings. The design of the FLC was carried out using the MATLAB-SIMULINK tool. Performance of the proposed control system was found to be better than the sample controller given in the benchmark problem. The proposed controller is less sensitive than the sample controller for the variation in the stiffness of the structure.

4. SUMMARY AND CONCLUSIONS

Genetic Algorithms are search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search.

Genetic algorithms were extensively applied to the problem of optimization of structures. The application of genetic algorithms in the field of structural optimization proved to be in increased growth during the last few years such that, in the last year considerable number of articles is observed in the literature in all categories of applications considered. Various fields of optimal structural design attract the application of genetic algorithms which increase year after year. In 1994 and later, only one field was considered (optimal design of steel structures) while five categories of fields are reported for year 2004. As reported by several investigations, genetic algorithms are the most effective and widely used techniques among other evolutionary algorithms as simulated annealing, differential evolution….etc,

Genetic algorithms proved to be efficient, accurate reliable and robust when applied to structural optimization problems. For various applications of optimum structural design, the use of genetic algorithm produces better solution than other methods, if any, especially in case of multiobjective optimization problems having many constraints and extensive design variables.

Modifications were applied to the standard genetic algorithm procedure to improve its exploration capability and produce better convergence. These modifications include the use of real coded genetic algorithm, the use of adaptive penalty to represent constraints, the application of two and three tournament selection or the Pareto set filter to deal with multiobjective optimization problems (MOP) and the use of parallel genetic algorithm for more economic computations.

Two main drawbacks of genetic algorithms can be observed when applying to structural optimization problems.

- ☑ The first is that GA is not theoretically guaranteed optimization method and that the optimality of its results is not verified. Such drawback can be ignored as most structural optimization problems are discrete, extensively constrained, and may converge to locally optimal regions; which make traditional optimization methods fail to deal with them. This makes no method exists for optimization of structural design problems and the "near optimum" obtained by using genetic algorithms can be, in most cases, the best solution.

- ☑ Genetic algorithms are computationally expensive when applied to structural optimization problems. Extensive computational effort is needed especially for calculating the fitness of individuals which may be carried out by means of numerically expensive methods such as the finite element. Improvements can be made on the computational efficiency by using more simplified structural models (even approximate) and using new techniques in applying the genetic algorithms (e.g. parallel processing).

5. PROMIZING FIELDS AND SUGGESTED AppLICATIONS

The application of genetic algorithm in the field of optimum structural design stills an open area of research, which can extract new fields and techniques. In this section samples of such promising areas and applications for which the application of genetic algorithm may be efficient are briefly presented.

Optimization of High Rise Buildings Using Genetic Algorithm

The selection of lateral load resisting elements of high rise buildings is a major and effective stage of structural design. Selecting the lateral load resisting system of high rise building can be done using genetic algorithms in terms of:

- ★ Optimization the behavior of buildings subjected to lateral loads by selecting the appropriate lateral load system.

- ★ Minimizing the eccentricity of lateral load in asymmetric-plan buildings by altering the distribution of structural elements.

Genetic Algorithm Optimization of earth Structures and foundations

Optimization of soil structures is of most importance due to the high material and construction costs. Genetic algorithms can be applied in different types of earth structures such as:

- ★ The optimization of retaining wall in terms of minimum volume subjected to stability and strength constraints. Dimensions of the wall represent the design variables to be evaluated.

- ★ Optimization of arrangement of piles supporting mat foundation.

Application Of Genetic Algorithm For Optimum Retrofitting Of Buildings

Due to the increased need for retrofitting of existing buildings and the high costs of such retrofitting, minimization of retrofitting cost and/or time are required by:

- Selecting the suitable method of retrofitting
- Choosing elements for which retrofitting takes place.

Optimum Design Of Cable Stayed Bridges Using Genetic Algoruthm

In the field of analysis and design of cable stayed bridge, different parameters can be used as design variables to perform multioptimization of costs, defection and stability of the bridge. Suggested design variables include arrangement of cables, pylon shape, deck type, and pylon-deck connection type.

Genetic Algorithm Optimization of Stiffened Plates

In stiffened plates, balanced design of slab and web is required. The arrangement of ribs together with the slab thickness can be considered as the design variables. The total cost is the objective function (fitness) subjected to deformations, strength and buckling constraints.

Improving The Efficiency Of Genetic Algorithm

As the major drawback of genetic algorithm is the computation effort as result of fitness calculation, new strategies are needed to improve the efficiency of genetic algorithm as:

- Development of more reliable approximate methods in structural analysis to replace current tedious numerical methods.
- Use of more efficient techniques to improve the convergence and reduce the cost of genetic algorithm as parallel GA.

6. REFERENCES

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