T.C.
ERCIYES UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
DEPARTMENT OF CIVIL ENGINEERING

MULTI-SOLUTION STOCHASTIC OPTIMIZATION ALGORITHM FOR STRUCTURAL MODEL UPDATING

Prepared by
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Supervisor
Assist. Prof. Dr. Müslüm KILINÇ

M.Sc. Thesis

July 2018
KAYSERI

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The thesis **Multi-Solution Stochastic Optimization Algorithm for Structural Model Updating** was prepared in accordance with Erciyes University Graduate Thesis Proposal and Thesis Writing Directive.

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ACCEPTANCE AND APPROVAL PAGE

This work, entitled: **"Multi-Solution Stochastic Optimization Algorithm For Structural Model Updating"**, which has been prepared by **Pa Amat MANNEH** and supervised by **Assist. Prof. Dr. Müslüm KILINÇ,** in the major of Civil Engineering of the Institute of Science and Technology of Erciyes University, has been accepted as a Master of Science Degree thesis by our jury whose identifications and endorsements are given below.

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APPROVAL

The acceptance of this thesis has been approved by the decision of the Executive Board of the institute with the 24/07/2018 date and 2018/32/09 numbered decision.

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Prof. Dr. Mehmet AKKURT

Director of institute

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MULTI-SOLUTION STOCHASTIC OPTIMIZATION ALGORITHM FOR STRUCTURAL MODEL UPDATING

Pa Amat MANNEH

Erciyes University, Graduate School of Natural and Applied Sciences
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Supervisor: Asst. Prof. Dr. Müslüm KILINÇ

ABSTRACT

Stochastic optimization plays a vital role in the design, operation and analysis of systems. To optimize means to find the best solution to a certain design problem. Stochastic Optimization methods have been used as vital tools in various fields like engineering, science, computer science, business, and statistics. Several research have been carried out on this topic. The purpose of this research is to use Multi Solution Stochastic optimization methods to find the best possible solution in determining the best structural model. With the availability of different optimization algorithms and techniques, the idea of model updating has become easier to undertake. Structural Engineers as in other engineering fields are usually faced with the task of reducing the amount of noise and vibration, increase lifespan and efficiency of structures. Due to their broad application in structural health monitoring, model updating techniques have been used by civil engineers in recent years. In this work, Multi-solution stochastic optimization method was be employed on a structural experiment model which was created at Erciyes University Civil Engineering Laboratory and also on some well-known benchmark problems. The Stochastic Optimization code is accomplished by adding operators to traditional genetic algorithms. With Multi-solution Optimization better results will be obtained.

Keywords: Multi-Solution, Stochastic Optimization, Model Updating.

YAPISAL MODEL GÜNCELLEME İÇİN ÇOKLU ÇÖZÜMLÜ RASTGELE OPTİMİZASYON ALGORİTMASI

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Erciyes Üniversitesi, Fen Bilimleri Enstitüsü
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ÖZET

Rastgele optimizasyon sistemlerin analizinde, işlemesinde ve dizaynında çok önemli rol oynar. Optimize etmek belirgin bir dizayn probleminde en iyi sonucu bulmak anlamına gelir. Optimizasyon metodları mühendislik, fen bilimleri, bilgisayar bilimleri, işletme ve istatistik gibi çeşitli alanlarda çok önemli araç olarak kullanılmaktadır. Bu konu hakkında çeşitli araştırmalar yürütülmektedir. Bu araştırmanın amacı çoklu çözümlü rastgele optimizasyon metodunu kullanarak mümkün olan en iyi sonuçları bularak en iyi yapısal modelin belirlenmesini sağlamaktır. Kullanılabilir farklı optimizasyon metodları ve teknikleri ile model güncelleme uygulamaları daha kolay şekilde yapılabilmektedir. Yapı mühendisliği diğer mühendislik alanlarında olduğu gibi sıklıkla yapıların etkinliği ve ömrünü arttırmak, gürültü ve titreşimi azaltmak gibi sorunlarla yüzleşmektedir. Yapısal sağlık takibinde geniş uygulama alanlarından dolayı, model güncelleme teknikleri inşaat mühendisliğinde yıllarca kullanılmaktadır. Bu çalışmada, geliştirilen çoklu çözümlü rastgele optimizasyon metodu geliştirilip, Erciyes Üniversitesi İnşaat Mühendisliği Bölümü labarotuvarlarında oluşturulmuş yapısal deney modellerinde ve bilinen örneklerde kullanılmıştır. Rastgele Optimizasyon Algoritması geleneksel genetik algoritma değiştirilip bazı ara işlemler eklenerek oluşturulmuştur. Bu algoritma ile daha iyi sonuçlar elde edilmiştir.

Keywords: Çoklu Çözüm, Rastgele Optimizasyon, Model Güncelleme.

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MULTI-SOLUTION STOCHASTIC OPTIMIZATION ALGORITHM FOR STRUCTURAL MODEL UPDATING

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbol	Description
PGSL	Probabilistic global search Lausanne
SA	Simulated Annealing
FDSA	Finite difference stochastic approximation
SPSA	Simultaneous perturbation stochastic approximation
GA	Genetic Algorithm
ACO	Ant colony optimization
PSO	Particle swarm optimization
Lbest	local best
Gbest	Global best
N	Number of particles
C_1	Cognitive parameter
C_2	Social parameter
TS	Tabu Search
ABC	Artificial Bee Colony
SN	Swarm Size
DOF	Degree of freedom

INTRODUCTION

With the availability of different optimization algorithms and techniques, the idea of model updating has become easier to undertake. Structural engineers as in other engineering fields are usually faced with the task of reducing the amount of noise and vibration, increase lifespan and efficiency of structures.

In the past decade, several model updating methods have been proposed in order to reconcile mathematical models with experimental modal data [23]. The mathematical models are usually finite element models that are discretized. There is no specific method of model updating that is universally accepted in solving model updating problems since every method has its own advantages and shortcomings. Model updating has been very useful in predicting structural damages through the construction of theoretical models of the structures to be considered. In the field of structural health monitoring, many researches have been centered on the detection and localization of damage in structures [22]. Checking the stiffness properties of elements can help in determining the size of the damage and also the damage location.

Over the past years, different optimization algorithms and techniques have found its usefulness in updating finite element models of structures to give better dynamics of structures. Due to their broad application in structural health monitoring, model updating techniques have found its place in civil engineering works in recent years [2]. Stochastic optimization has been useful in the design, operation and analysis of systems.

Optimal model estimation is sensitive to uncertainties which is because of mathematical models' limitations used in representing the way in which a real structure behaves, noise measurement that comes from ambient excitations and processing errors that occur in the estimation of modal data. The estimates of optimal model can also be sensitive to the amount and type of the calculated modal data that is used for the reconciling process, in addition to the norms used in fit measurement between the model predicted and the measured modal properties.

To optimize means to look for the best possible solution to a certain design. In nature, human beings as well as animals and plants engage in optimization process. For instance, optimization is used by animals in minimizing the path for finding food or in some cases maximizing their energy for hunting. Optimization's mathematical representation refers to the minimization or maximization of scalar-valued objective function with respect to a vector with design parameters.

Stochastic methods of optimizing have been used as vital tools in various fields like engineering, science, computer science, business, and statistics. Stochastic methods of optimization comes with some advantages among them is that it provides a way of coping with noise system that is inherent and also with systems and models which are highly dimensional, highly non-linear, or with systems that are not appropriate for classical deterministic optimization methods. Since solution methods usually depend on the problem structure, Lauren A. Hannah [1] solution methods were based on the type of problem and the solution methods associated with it. The single stage problems and multi-stage problems were the two prominent division that were taken into consideration. In this thesis, stochastic optimization methods will be applied to obtain the best solution in determining the best structural model.

CHAPTER 1

GENERAL INFORMATION AND PREVIOUS WORKS

1.1. Model Updating

Sarvi et al [22] presented a method which is efficient in updating structural finite element model. Sarvi et al [22] used an enhanced Levenberg Marquardt algorithm which is centered on sensitivity analysis and has the ability of coming up with linear solution in the case of non-linear damage detection problems. Sarvi et al used the Levenberg Marquardt algorithm to carry-out model updating by minimizing the difference of the acceleration of the real damage that is recorded and that of the hypothetical damage structure [22]. Model updating is used to monitor the condition and checking the lifespan of bridges with the help of free and ambient vibration measurement which comes from wind and traffic [25]. A proposed model updating methodology for finite element is tested on a bridge at kavala (Greece) utilizing the measured acceleration data which comes from traffic load events [25]. A multi-objective identification technique which results in multiple Pareto optimal structural model based on modal residuals is presented. Heung-Fai Lam and Jia-hua yang tried to tackle high modelling error in structural diagnosis by presenting a Bayesian model updating and prediction of vibration [24].

1.2. Optimization

Optimization deals with the process in which best results can be obtained under given circumstances. When it comes to the design, construction or even maintenance of engineering systems, the tasks faced by engineers at several stages vary from technological to managerial decisions. One of the main aim of optimizing is to help in minimizing the effort that would be required or it might be for the maximization of the desired benefit.

1.3. Application of Optimization in Engineering

Optimization's application in engineering have been very useful in solving virtually any engineering problem. Optimization has become so important that it is use in almost all engineering fields [6]. It is use in determining the minimum weight when designing an aircraft and aerospace structures. Space vehicle's optimal trajectory can be determine with the help of optimization. In the field of civil engineering, optimization can aid in the design of civil engineering structures like frames, bridges, towers, dams etc. for determining the minimum cost. It can also be used to help in the design of structures and determining the minimum weight of these structures for wind, earthquake and other random loadings. In the field of water resources engineering, it is used to design water resources systems so as to obtain maximum benefit. Another application of optimization is that it can be in plastic design of structure to obtain optimal design. For the design of mechanical components like machine tools, gears, cams etc. Optimization can be used for the optimal design of such mechanical components. In the case of selecting the condition of machine for the process of metal-cutting, optimization can be used in determining the minimum cost of production. Optimization can be used in designing of trucks, cranes, conveyors and other material handling equipment so as to obtain minimum cost. For obtaining maximum efficiency of pumps, turbines and equipment used for heat transfer, optimization can be used in the design phase. In the field of electrical engineering, Optimization can aid in the design of electrical machineries like generators and transformers.

The above outlined application of optimization in different engineering fields shows how optimization has taken the lead in solving engineering problems. For the past years, many algorithms have been developed and each of these tries to obtain the best possible result of engineering problems.

1.4. Scope Of The Thesis

As in other engineering fields, optimization is an important tool used in structural modelling. The objective of the research is to come up with a stochastic optimization algorithm for finding the best solution in determining the best structural model. The proposed algorithm is to be tested on some benchmark problems and the results will then be compared with results obtained from other methods to evaluate and see how effective the method of stochastic optimization proposed is before employing it on a structural experiment model which was created at Erciyes University Civil Engineering Laboratory.

CHAPTER 2

MATERIALS AND METHODS

2.1. Model Updating

The aim of model updating is to modify the system parameters of a theoretical model in a way that the model describes the structural behavior of a considered mechanical system as good as possible. Model updating techniques' way of improving the predictions of the actual structure's behavior is through the identification and correction of the parameters of the analytical model that is deemed uncertain. In recent years, structural engineers have given significant attention to model updating.

In order to obtain desired results and performance of model updating several factors need to be taken into consideration. Among them are the chosen objective function, the optimization method, respective parameters controlling the optimization algorithm and the choice of parameters to be modified. Brehm and Zabel used several objective functions and optimization techniques in updating a model with respect to data obtained from dynamic tests of a 3 degree of freedom (3 dof) of a mass spring system [4]. Due to uncertainties that comes with the experimental data and the influence they can have on the system parameters, stochastic model updating was applied, the results of which shows the importance of choosing an appropriate objective function for a stochastic model updating .

The model updating methods that are used currently can be categorized into two broad groups. These two main groups are the direct methods and the sensitivity based methods [21]. The direct method's main disadvantage is that when it tries to force the model updating procedure in producing the exact measured modal data then the measurement errors can be transferred to the parameters. Drawback like this makes the direct methods been used rarely in structural dynamics. Recently, sensitivity-based methods have become the most popular methods due to the fact that they are not subjected to limitations like the direct methods.

The model updating problems are shown as the optimization problem in the case of the sensitivity-based methods. The objective function is the errors between experimental and analytical data. The minimization of the objective function is done in a way that the physical parameters that are present in the finite element model are adjusted resulting in the minimization of the objective function.

2.1.1. Model Updating Procedure

Model updating procedure generally includes three aspects [18]. The first aspect is selecting responses to serve as reference data. These response data are the data measured and which are often the measured mode shapes and frequencies. Then parameters which are uncertain and sufficiently sensitive to changes of the selected responses are selected. The third aspect is model tuning. It is an iterative process which depending on the reference data selected helps in the modification of the selected parameters.

2.2. The Modal Assurance Criterion (MAC)

MAC is a method used to numerically measure the similarity between two modes. For many years now, it has been used in measuring the correlation between modes shapes of analytical and experimental [26]. The correlation between analytical and experimental data is an important part of the structural dynamic characterization and updating of systems. Mac considers mode shapes only and for this reason a separate comparison of frequencies must be used which is in conjunction with the MAC values so as to determine the mode pairs correlated [26]. Here, the modal vectors contained in two different normalized modal matrixes are compared. As a result, the mode shapes most similar to each other among the mode-shaped vectors contained in the two different mode-shaped matrices are revealed.

$$MAC(i,j) = \frac{\left|\{\Phi_A\}_i^T \{\Phi_B\}_j\right|}{\left(\{\Phi_A\}_i^T \{\Phi_A\}_j\right)\left(\{\Phi_B\}_i^T \{\Phi_B\}_j\right)} \tag{1}$$

In this expression, Φ_A and Φ_B are two different mode matrices, which are composed of normalized mode-shaped vectors. All of the modal vectors in these two matrices are compared with each other and the most similarities are revealed as a result.

2.3. Objective Function For Model Updating

For the past years, engineers and scientist have developed different model updating methods but updating a model is still a difficult problem due to the fact that model updating usually has non-linear characteristic and also the fact that it is an inverse process. Due to these reasons, model updating heavily depends on the chosen objective function and the parameters used in the process of updating a model. Usually the objective function is set as a function which involves the differences of the weighted sum between the analysis results of the analytical and experimental [27]. Selecting the weighting factors is usually difficult because the importance among the relative measured data is specific for each problem and not obvious. For example, the fundamental natural frequency difference may be overweighed in the objective function such that the other updated differences such as second natural frequency, mode shapes are not fit satisfactorily or vice versa.

2.4. Error function

Error function in probabilistic interpretations means the maximum likelihood. Error function is an actual loss function that you want to minimize. The idea of optimization comes to play for these interpretations [28]. The error function is obtained by integrating the normalized Gaussian distribution.

$$\operatorname{erf} x = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2}\, dt \tag{2}$$

Where the coefficient in front of the integral normalizes erf(∞) = 1. A plot of erf x over the range $-3 \leq x \leq 3$ is shown as follows.

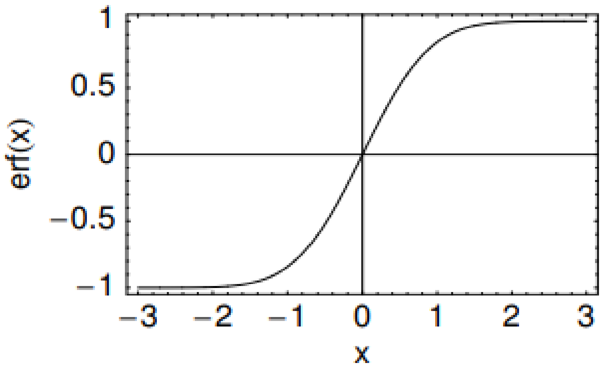

Figure 2.1. A plot of erf x over the range $-3 \leq x \leq 3$

The error function is defined for all values of x and is considered an odd function in x since erf x = −erf (−x).

2.5. Optimization Techniques

To find a method that works efficiently for all optimization problems is virtually impossible since each problem is different from the other. Over the years, scientists and engineers have developed several optimization techniques for solving optimization problems. Some of the optimization techniques used for solving optimization problems are explained in the sections to follow.

2.6. Why Stochastic Optimization

The process of minimizing or maximizing objective functions when there is randomness in one or more of the input parameters is what stochastic optimization is about. The word Stochastic itself means probability or involving chance. In most cases, there exist uncertainties in real world engineering structures which makes the stochastic optimization techniques the most viable to update such models.

2.7. Stochastic Methods

Stochastic optimization refers to the different methods of maximization or minimization of an objective function in the presence of randomness. The stochastic method of optimization was used in obtaining the optimum design of truss structures [3]. After testing the PGSL on the well-known ten bar truss optimization, the results that were obtained were then compared with the ones obtained by others metaheuritics. In recent years, most of the finite element methods for model updating investigated have been deterministic since the presence of uncertainties in parameters and measurements are not put into consideration [5]. For real-world engineering structures and practical point of view, stochastic model updating can be of great importance in dealing with uncertainties in parameters and measurements.

2.7.1. Simulated Annealing

Simulated annealing refers to a random-search technique which exploits a relationship in which a metal cools and freezes to result in a minimum energy crystalline structure (the annealing process) and the searching of a minimum in a more general system; it forms the foundation of an optimization technique in dealing with combinatorial and other problems**.** It was developed in 1983 with the aim of dealing with highly nonlinear problems**.** Simulated annealing's ability to avoid becoming trapped in local minima gives it advantage over other optimization techniques. Both the changes that decrease the objective function (in case of minimization) and changes that increase the objective function are accepted with SA algorithm. The objective function is increased by changes that have a probability:

$$p = \exp(-df / T) \tag{3}$$

where df denotes the increase in f and the control parameter is denoted by T, which with the original application by analogy is known as the system "temperature" irrespective of the objective function involved. Figure 2.1 shows a flow chart of simulated annealing.

Simulated annealing has the ability of dealing with highly nonlinear models, noisy data and chaotic and many constraints. An advantage of SA is its robustness and the fact that it is a general technique. The advantages SA has that other local methods lack is its flexible nature and the ability of SA in approaching global optimality. It is termed as a versatile algorithm because it is independent of any restrictive properties that the model might possess. The ‘’tuning’’ of SA methods is easy. When dealing with stochastic or nonlinear systems that are reasonably difficult, the best approach is to ‘’tuned’’ a given optimization algorithm so as to be able to enhance its performance. To tune an algorithm that would be used in different problems is not an easy task because it takes time and effort to be able to get familiar with a given code [8].

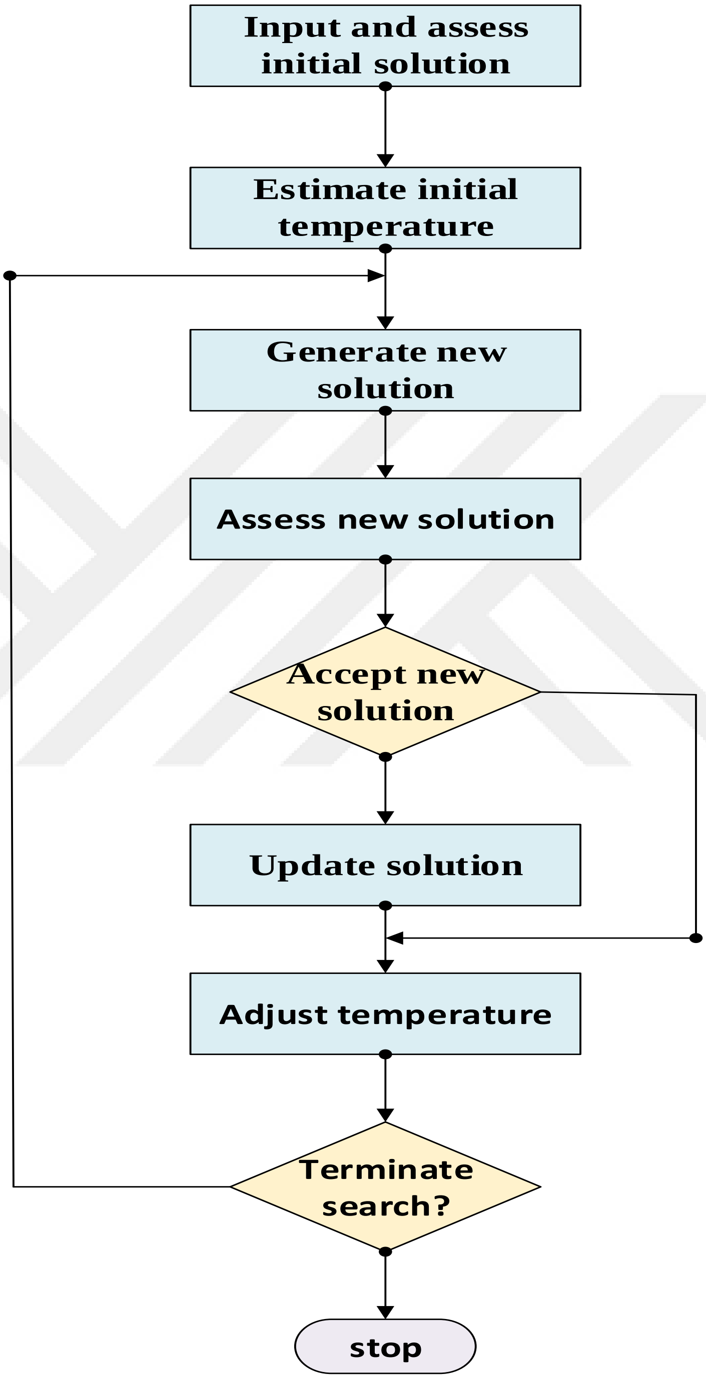

Figure 2.2. The structure of the simulated annealing algorithm

2.7.2. Stochastic Approximation

Stochastic approximation is a cornerstone of stochastic optimization. Stochastic approximation was first introduced by Robbins and Monro (1951) as a root finding technique in situations where the only available measurements are the noisy measurements.

$$\theta_{k+1} = \theta_k - a_k g(\theta_k) \tag{4}$$

Where gk(θk) is the estimate of the gradient g(θ) at iteration k and ak is a scalar gain sequence satisfying certain conditions. Unlike any steepest (gradient) descent method, stochastic approximation assumes no direct knowledge of the gradient. To estimate the gradient, there are two common stochastic approximation methods: finite difference stochastic approximation (FDSA) and simultaneous perturbation stochastic approximation (SPSA) [7]. FDSA adopts the traditional Kiefer-Wolfowitz approach to approximate gradient vectors as a vector of p partial derivatives where p is the dimension of the loss (fitness) function.

2.7.3. Genetic Algorithms

In the 1960s John Holland invented Genetic algorithms which were later developed in the 1960s and the 1970s by Holland, his colleagues and students at the University of Michigan. Genetic Algorithms (GAs) are adaptive heuristic search algorithm which are based on the evolutionary ideas of natural selection and genetics. As such they represent an intelligent exploitation of a random search used to solve optimization problems.

For example, two offspring 10011111 and 11100100 could be produce after the strings 10000100 and 11111111 are crossed over after the third locus in each.

2.7.3.1. GA Operators

The genetic algorithm in its simplest form involves three types of operators: crossover, selection and mutation.

Selection: This operator deals with the chromosome selection in the population for reproduction. The likelihood of a chromosome to be selected for reproduction depends on its chromosome.

Crossover: The crossover operator deals the choosing of a locus randomly and exchanging the subsequences before and after that locus between two chromosomes to create two offspring. For example, given the two strings 11111111 and 10000100 which could be crossed over after the third locus in each so that two new offspring 10011111 and 11100100 would be produced. The concept of biological recombination between two chromosome organisms is being imitated by this operator [17].

Mutation: With a mutation probability mutate new offspring at each position in chromosome. For example, the string 00000100 could be mutated at its second position to yield 01000100 There is usually a very small (e.g. 0.001) probability of mutation occurring at each bit position.

Below are the steps for a general GA process

1. Initialization: In the initial step, a population of n chromosomes (candidate solutions to a problem) is generated

2. Evaluation: A fitness function is used to evaluate every solution. The solution should now adapt to this fitness function which acts as an environment.

3. Selection: In this step the selection of solutions that are best adapted to the environment for reproduction is done. Two parent chromosomes are selected from a population depending on their fitness, with the better fitness having the better chance to be selected.

4. Crossover: From this crossover, new offspring will be created.

5. Mutation: For the step, with a mutation probability there is mutation of new offspring for every position in chromosome.

6. Population replacement: In this step, the old solutions are replaced with new solutions.

7. Termination: Starting with initialization, all the steps that follows will be repeated until a termination condition is fulfilled.

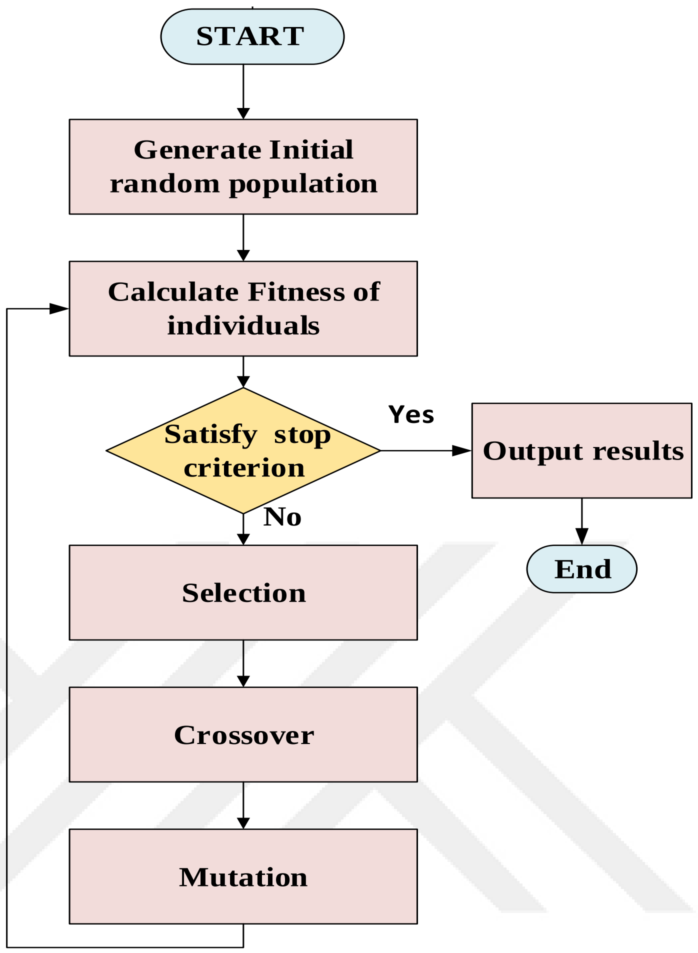

Figure 2.3. Genetic algorithm flowchart

2.7.4. Ant colony optimization (ACO)

This optimization technique was introduced first in the early 1990s. The Ant colony optimization got its inspiration from the observation of ant colonies. Among the behaviors of the real Ant colonies that inspired the ACO is the foraging behavior of ants and particularly the way ants find the paths between their food sources and nest. The behavior of the real ant colonies is exploited in the artificial ant colonies in so as to obtain approximate solutions to optimization problems.

The ACO algorithm has found a place in engineering works involving optimization. ACO was applied by O. Hasançebia and S. Çarbaş to determine the size optimum design of pin-jointed truss structures [13]. To detect and to quantify structural damages based on modal parameters, the ACO was used in [14]. Figure 2.3 is an illustration of a how the ACO algorithm works.

2.7.5. Particle swarm optimization (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization technique which was developed by Dr. Eberhart and Dr. Kennedy in 1995, the inspiration coming from the way birds flock or the schooling of fish. Optimization in PSO is done by optimizing an objective function in a population-based search approach. The potential solutions within the population are termed as particles, which is a metaphor of birds in flocks. The particles are initially randomly initialized and are free to fly across the multidimensional search space. The difference between the approaches of the particle swarm optimization and the GA is that with PSO are no genetic operators such as mutation and crossover. In PSO, particles update themselves utilizing the internal velocity, they also have a memory that the algorithm uses. For the case of PSO, information is given out to others by only the best particles which makes it a one-way information mechanism. The evolution only searches for the best possible solution.

The idea of using Particle swarms hasn't been used in structural engineering field until very recently. This optimization method has shown promising results when applied on structural optimization. Particle swarms have found its place in the field of structural optimization very recently due to the recent wide spread use of optimization in solving engineering problems and they have showed results which promising especially in areas like the structural shape optimization.

In the simplest form of PSO, there is movement of each member of the particle swarm through a problem space by two elastic force. One of the forces attracts it with random magnitude to the best location that the particle encounters known as Lbest (local best), while the other force attracts it to the best location that is encountered by any member of the swarm with random magnitude known as Gbest (global best). Each particle's velocity and position are updated for every time step until the whole swarm converges to an optimum [15]. The original PSO formulae as described in [16] are:

$$V_i^{t+1}=v_i^t+c_1r_1^t(P_i^t-x_i^t)+c_2r_2^t(P_g-x_i^t) \qquad (5)$$

$$x_i^{t+1}=x_i^t+V_i^{t+1} \qquad (6)$$

Where:

- i= (1, 2, 3…………, N), where N denotes the number of particles.

- c_1 and c_2 represent the positive constants which are the cognitive and social parameters, respectively.
- r_1^t and r_t^2 are random vectors that have components that are uniformly distributed in (0, 1).
- $X_1^t = (x_1^t, x_2^t ....X_D^t)$, shows the location of the i^{th} particle at t^{th} iteration, and D is the number of design variables.
- $V_i^t = (V_1^t, V_2^t, ...V_D^t)$, shows the velocity vector of the i^{th} particle at t^{th} iteration.
- $P_i^t = (P_1^t; P_2^t, ...P_D^t)$ shows the best previous position vector of the i^{th} particle at t^{th} iteration.
- $P_g = (P_1, P_2, ...P_D)$, the symbol g denotes the best particle's index among all the particles that are in the population.

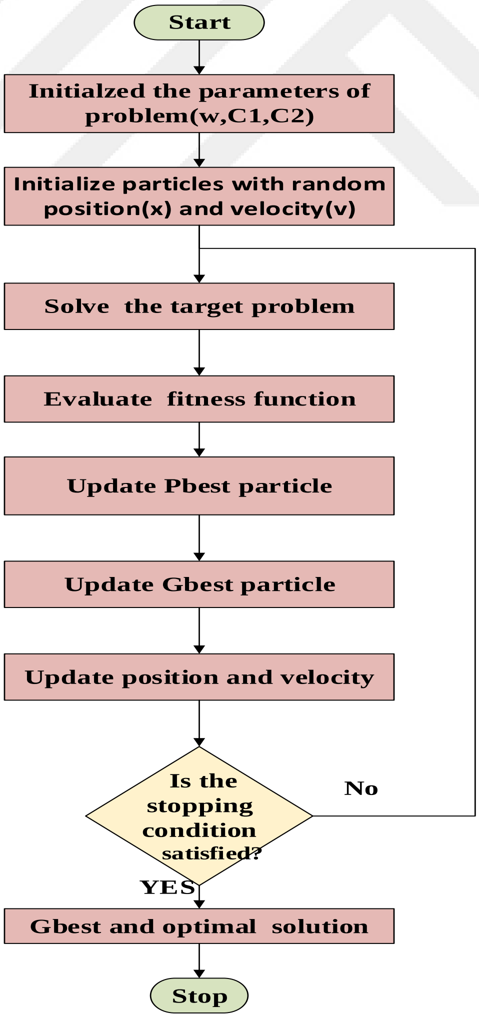

Figure 2.4. Particle swarm optimization flowchart

2.7.6. Tabu Search Method

Tabu Search is a type of meta-heuristic which is used to solve optimization problems. It helps a local heuristic search procedure in exploring the solution space that is beyond local optimality. The adaptive memory designs of tabu search which is one of its main components, provides it with a more flexible search behavior. Tabu Search method can be applied on different types of optimization problem. Most of these optimization problems can be stated as follows [9]:

Optimize f(x) subject to

$x \in X$

Where ‘’optimize’’ refers to minimize or maximize, the function f(x) can be linear, nonlinear or stochastic, and the set X summarizes constraints on the vector of decision variables x.

Tabu search (TS) is used for the optimization of structures like the well-known ten bar truss and the results of which were compared to results published in other works [10]. Tabu Search method is also used for the optimization of skeleton structures [11].

2.7.7. Artificial Bee Colony (ABC)

Artificial Bee Colony refers to a population-based stochastic algorithm that has been tested on many optimization problems and demonstrated good search abilities [19]. The Artificial Bee Colony was proposed by Dervis Karaboga in 2005, inspired by the intelligent foraging behavior of honey bees [20]. The ABC algorithm is centered on the model that was proposed by Tereshko and Loengrov in 2005 for honey bee colonies [20]. The ABC algorithm comprises of three types of bees: employed bees, onlooker bees and the scout bees. The employed bees are task with the searching of food around the food source in their memory and the information that is gathered will then be shared to the onlooker bees. The onlooker bees engages in the selection of good food sources from the food sources which are found by the employed bees. The selection is done such that the food source having higher quality (fitness) tend to have a better chance of been selected by the onlooker bees than the ones with lower quality.

The ABC algorithm consist of two halves of the swarm with the first consisting of the employed bees while the second consist of the onlooker bees. The amount of solutions in the swarm is equivalent to the number of the onlooker or the employed bees**.**

Randomly distributed initial population SN solutions or food sources are generated by the ABC, with SN denoting the swarm size. Let the $_i$th solution that are in the swarm be represented by $X_i= \{X_{i,1}, X_{i,2},............,X_{i,D}\}$, in which the dimension size is denoted by D. A new candidate solution V_i is generated by each employed bee X_i in the neighborhood of Vi current position as follows:

$$V_{i,j}=X_{i,j}+\phi_{i,j}.(X_{i,j}-X_{k,j}) \qquad (6)$$

Where the randomly selected solution (i≠k) is represented by X_k, the random dimension index that is selected from the set {1, 2,.....,D} is denoted by j, and the random number that is within [-1,1] is denoted by $\phi_{i,j}$. A greedy selection is used after generating the new candidate solution Vi. The fitness value of Vi is compared to its parent X_i and if V_i is better than X_i then X_i is updated with V_i, otherwise X_i is kept unchangeable.

After the search process is completed by all the employed bees, the information taken from their food source is then shared with the onlooker bees through the process of waggle dances. The information that is taken from all employed bees is evaluated by an onlooker and the onlooker will then choose a food source having a probability relating to its nectar amount.

2.8. Development of the Stochastic Optimization Algorithm

This proposed algorithm will help deal with structural optimization and model updating problems with the help of a multi-solution approach.

2.8.1. How the Stochastic Optimization Algorithm Works

The algorithm works with first creating an initial random population. Since the search space might be big which can require time and makes it harder for a better solution to be found by the algorithm, sub-groups will be created within the search space. Individuals will go to the sub-group within the search space with better solution.

For instance, let's say students were ask to find a particular class in a school with lots of classes .It would be difficult to find the class if all the students head in the same way to search for the class but instead students would divide themselves into groups and head to locations with higher probability of finding the class. The locations with less probability of finding the class will then be allocated with less students while locations with higher probability will be allocated with more students. In this way, the students will keep on searching until the class is found. Here the classes corresponds to the solutions while the students corresponds to the individuals in the population.

The procedure of the stochastic method algorithm comprises of the steps below:

Step 1: Specify the optimization problem and parameters of the algorithm.

Step 2: The population is then randomly initialized

Step 3: Evaluate fitness of members of the population

Step 4: Create sub-groups

Step 5: Evaluate the fitness of members of the sub-groups.

Step 6: Repeat Steps 3 and 4 until the termination criterion is satisfied

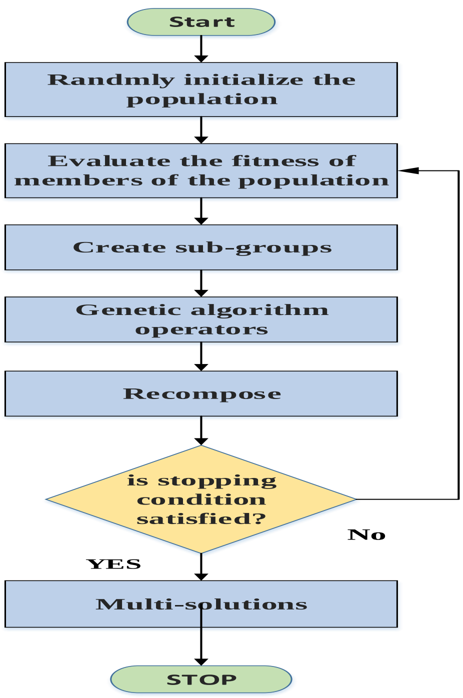

Figure 2.5. Flowchart of the Stochastic Optimization

CHAPTER 3

CASE STUDIES FOR NUMERICAL APPLICATION

3.1. CASE 1: Gaussian Function

Gaussian Function was used as a test function to evaluate how effective the stochastic optimization code used in this work is. The Gaussian function is a continuous function which helps to approximate exact binomial distribution of events. In some real observations, the Gaussian function provides probability for them to fall between any two limits or predefined real numbers as the function tends to zero on either side. The graph of a Gaussian is a characteristic symmetric "bell curve" shape as shown in figure 2. The height of the curves was set as 5, 3.5 and 5.5.

After several runs of the stochastic optimization code, the best results was obtain with a population size of 1000 and with 30 groups. The generation was set at 50.

The results obtain are clearly shown in table 3.1. The results shows the effectiveness of the stochastic optimization code.

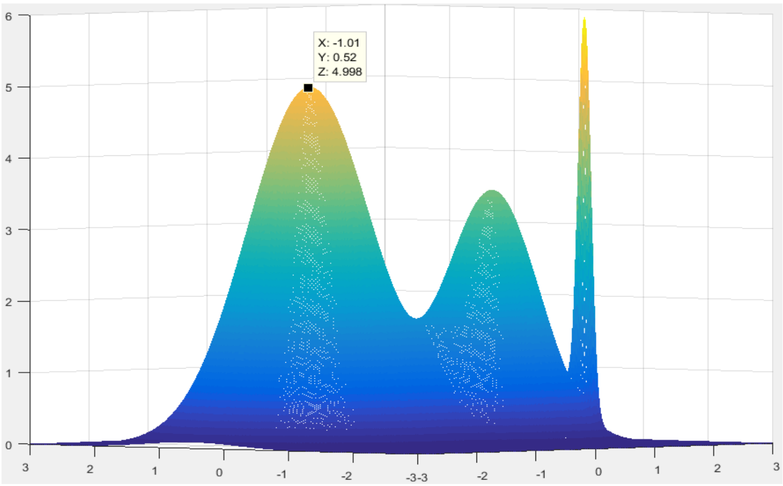

Figure 3.1. Gaussian function graph

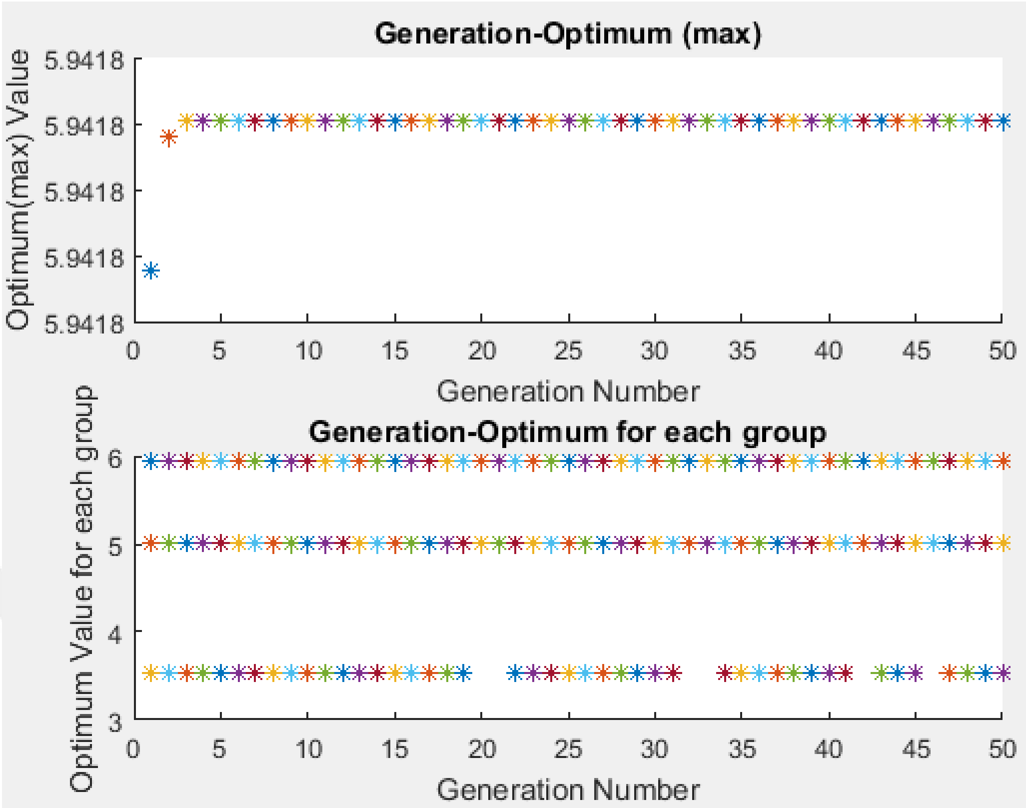

Figure 3.2. Matlab results of the Gaussian function

Table 3.1. Results of the Gaussian function

Height	X	Y
5.9418	1.9987	-0.9992
5.0009	-0.9995	0.4995
3.5347	0.9869	-0.4950

3.2 CASE 2: Crowned Cross Test Objective Function

In this example, the Crowned Cross global optimization problem is used as a test function for the stochastic optimization code. This is a multimodal minimization problem defined as follows:

$$f_{\text{CrownedCross}}(\mathbf{x}) = 0.0001\left(\left|e^{\left|100-\frac{\sqrt{x_1^2+x_2^2}}{\pi}\right|}\sin(x_1)\sin(x_2)\right|+1\right)^{0.1} \tag{7}$$

The number of dimension is denoted by n and $x_i \in [-10, 10]$ for i=1, 2. In this example, the population size was set at 200 with variable limits of 10 and -10. The number of groups for this problem was set at 20 and number of generations set at 200.

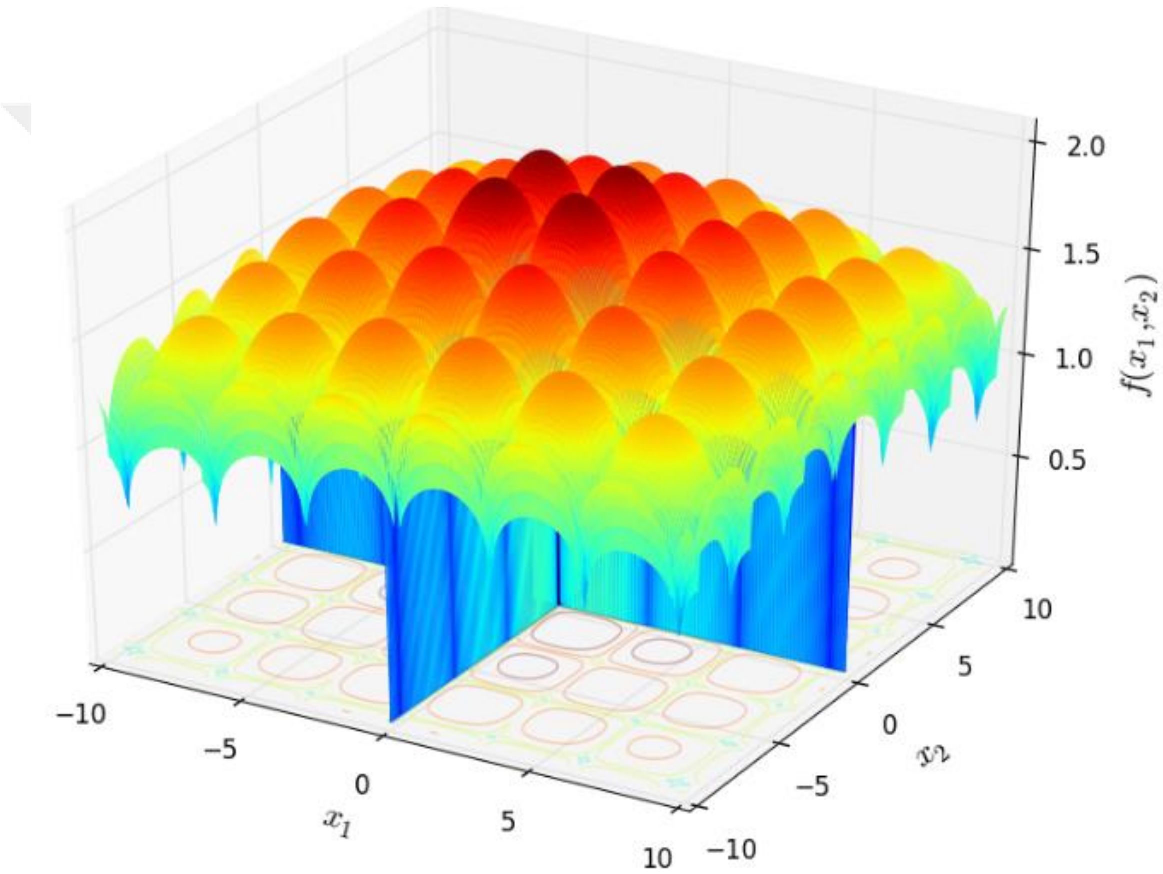

Figure 3.3. Two-dimensional Crowned Cross function

The results obtain for the Crowned Cross function shows a global optimum of 2.0626 for $x_i = \pm 1.349406608602084$ for i=1, 2. Once again the effectiveness of this stochastic optimization code is demonstrated. Since it's a multi solution algorithm, other possible results were also obtained as shown in table 2.

Table 3.2. Crowned Cross function Result

$f(x_1\ x_2)$	X_1	X_2
2.0626	-1.3494	1.3494
2.0626	1.3500	1.3497
2.0626	1.3501	-1.3496
2.0626	-1.3482	-1.3494
1.8899	1.4706	4.4168
1.8878	-1.6173	4.4123
1.8758	-4.0709	-1.5210
1.9584	2.3084	-1.3811
1.9435	2.3701	1.4179

3.3. CASE 3: Truss Design Example

In this section, a truss design example has been conducted with stress and deflection constraints: The population size is taken as 500 in all design examples and group number is taken as 20. In the all design examples.

3.3.1. The 10-Bar Truss

The problem to be considered with the stochastic optimization is a problem which is a well-known problem corresponding to a 10-bar truss non-convex optimization shown on Fig. 3.4. The minimization of this problem is done by optimizing the cross-sectional area for each of the 10 structural members with the cross-sectional area ranging from 0.1 to 40 in^2. With the stress and displacement used in the specification of constraints, an allowable stress of 25 ksi for both tension and compression and maximum nodal displacements in X and Y directions are limited to ±2 inches for all free nodes were considered. The material density is 0.1 lb/in3 and with Young's modulus of E = 10^4 ksi. In this design example, the loading condition is considered as: P1=150 kips and P2=50 kips.

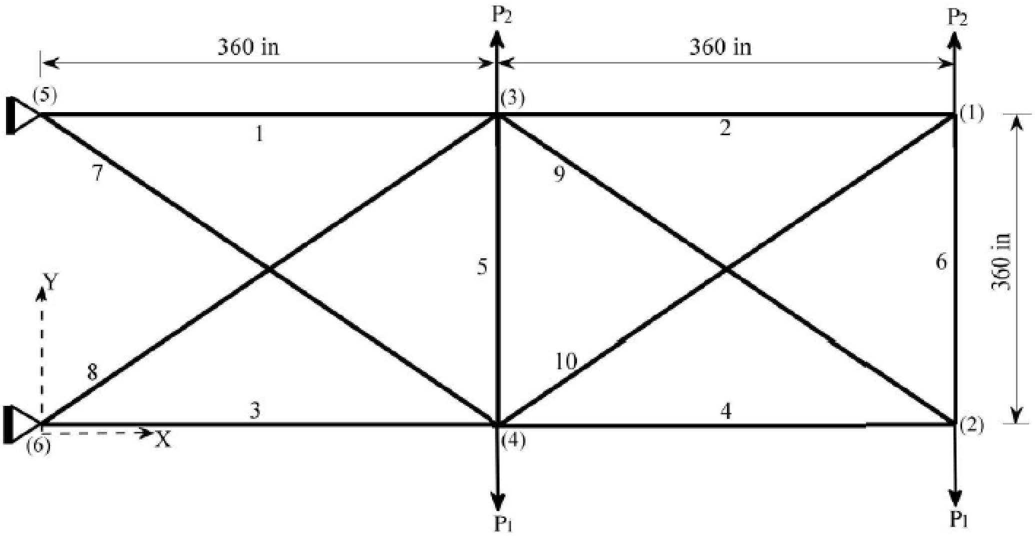

Figure 3.4. Scheme of the 10-bar planar truss.

In table 3.3., the results obtained by the stochastic optimization algorithm is shown. The stochastic optimization code provides us with multiple solution as shown in table 3.3. The optimum area of each member and the best weight of the whole structure is calculated. The optimization results of table 3.3 are those obtained by forming 20 groups of the total population.

Table 3.3. Optimization results of Case 3(group number 20)

Area(A) in^2										Weight(lb)
A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	
24,14	0,8	27,42	15,51	0,22	2,57	12,2	14,1	18,48	0,23	4835,33
24,22	0,79	24,06	13,87	0,23	3,51	12,83	13,2	23,15	0,45	4926,48
20,44	1,09	30,25	14,27	0,25	4,24	11,08	11,1	28,08	0,38	5117,76
20,33	1,92	30	17,55	0,33	3,06	12,39	14,28	22,92	1,33	5227,46
21,5	1,31	27,36	16,99	0,3	7,16	14,15	13,36	20,99	0,27	5169,08
25,31	5,23	26,87	17,54	0,34	4,47	11,72	13,15	21,07	1,28	5275,77
21,33	3,17	29,73	20,64	0,29	4,06	14,13	15,69	18,06	0,57	5318,38
31,1	0,56	21,54	14,72	0,44	4,21	15,08	15,31	19,17	2,76	5275,78
29,74	1,13	25,63	14,98	1,33	2,51	12,09	17,86	18,42	0,53	5201,21
27,67	2,48	20,47	13,1	0,21	8,14	18,51	14,79	22,12	6,09	5726,35

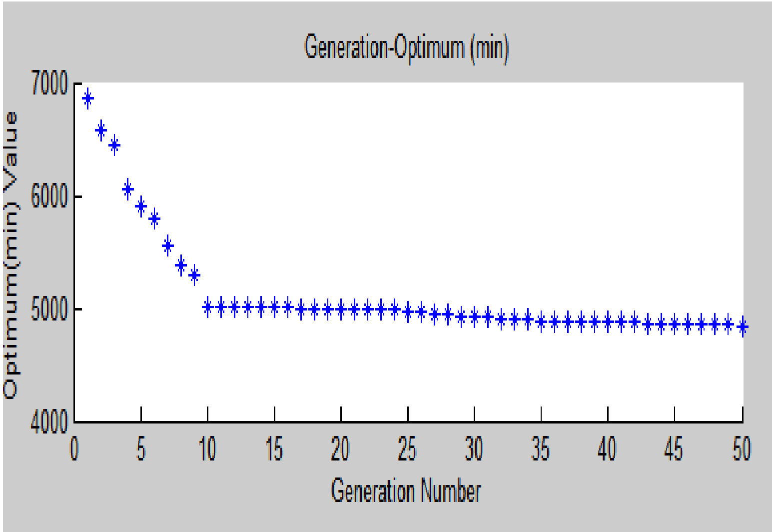

Figure 3.5. Matlab graph of optimum value vs. generation number Case 1(group number 20)

In table 3.4 and 3.5 shows the results obtained from population groups of 30 and 40 respectively. In table 3.6, comparison of the stochastic optimization code with other optimization methods is carried out. The stochastic optimization code provides us with multiple solution but only the best solution will be considered when making comparison with other methods as can be seen in table 3.6.

Table 3.4. Optimization results of Case 3(group number 30)

Area(A) in^2										Weight(lb)
A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	
21,88	0,61	27,38	14,91	0,13	2,61	12,14	13,36	20,49	0,24	4784,29
26,71	0,29	25,27	13,44	0,17	2,68	13,21	12,42	20,34	0,24	4820,79
23,24	0,52	25,7	16,16	0,16	3,67	11,78	11,21	23,3	0,16	4865,75
23,95	3,42	25,8	14,87	0,37	3,02	11,26	14,15	21,86	0,44	5000,12
26,49	0,94	26,06	10,99	0,12	5,51	12,41	11,87	23,46	0,34	4971,52
24,54	1,03	27,65	16,24	0,22	3,42	12,54	9,77	25,5	0,43	5086,88
24,91	1,16	26,86	16,11	0,24	2,64	12,87	13,34	21,94	0,43	5062,57
28,07	0,56	27,56	13,2	0,28	3,73	11,27	13,01	22,77	3,04	5193,67
22,11	4,49	29,37	10,15	0,37	3,47	11,03	15,79	25,68	0,53	5218,75
21,01	0,34	26,85	12,85	0,16	9,06	17,9	15,83	19,35	0,31	5247,3

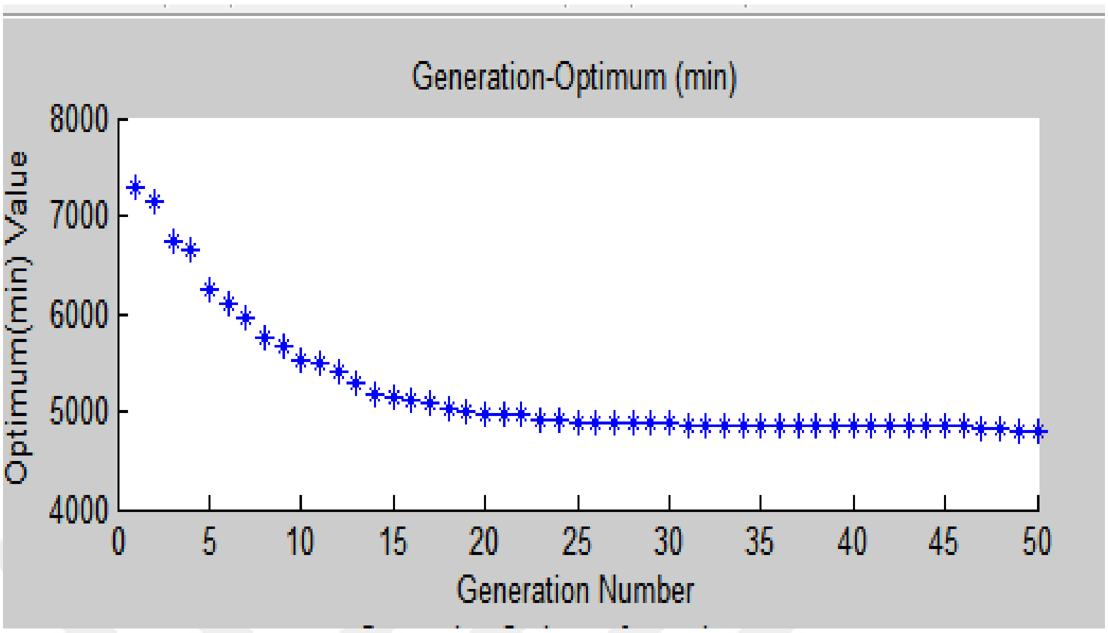

Figure 3.6. Matlab graph of optimum value vs. generation number Case 3(group number 30)

Table 3.5. Optimization results of Case 3(group number 40)

Area(A) in^2										Weight(lb)
A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	
25.31	0.3	27.5	15.4	0.1	1.9	12.4	13.6	17.7	0.24	4778.87
25.4	0.3	24.6	14.1	0.2	2.2	12.7	15.1	19.2	0.26	4812.85
26.04	0.6	27.4	13.1	0.1	4.1	12.7	13	18.9	0.29	4854.43
27.34	1.7	23.2	12.4	0.3	2.5	13.2	15.3	20	0.31	4909.61
23.16	1.3	26.7	13.8	0.2	2.9	13.7	14.6	19.5	0.38	4905.17
25.35	0.9	26.4	14.2	0.2	2.7	15	14.9	17.9	0.46	4966.04
23.25	0.6	23.6	15.1	0.4	2.1	14.1	16.9	19.8	0.41	4950.17
27.47	0.6	25.8	15.2	0.3	3	12.2	12.5	20.3	0.38	4914.62
21.37	0.1	25.7	13.1	0.2	2.5	13.2	16.8	21.3	1.44	4952.41
25.62	1.4	28	17.5	0.4	3.9	15	12	18	0.22	5099.74

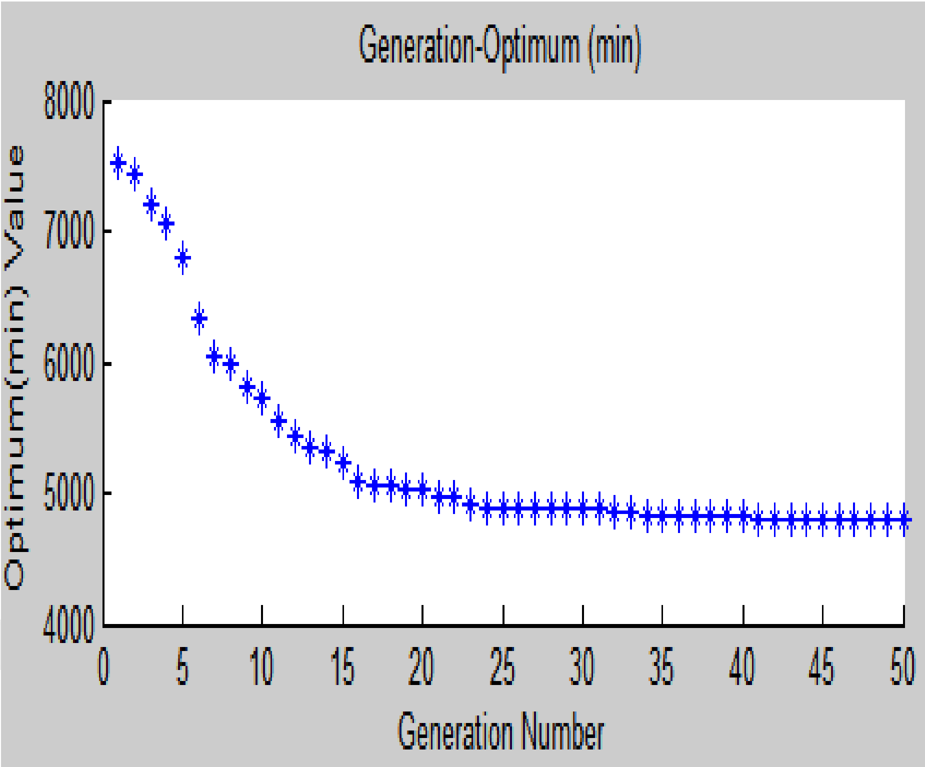

Figure 3.7. Matlab graph of optimum value vs. generation number Case 1(group number 40)

Table 3.6. 10-Bar Truss Optimization Results

Member Number	Schmit and Farshi (1974)	Schmit and Miura (1976)	Venkayya (1971)	Sedaghati (2005)	Li et al. (2007)	This work(30 group)
1	33.43	30.67	30.42	30.5218	30.569	21.88
2	0.100	0.100	0.128	0.1000	0.100	0.61
3	24.26	23.76	23.41	23.1999	22.974	27.38
4	14.26	14.59	14.91	15.2229	15.148	14.91
5	0.100	0.100	0.101	0.1000	0.100	0.13
6	0.100	0.100	0.101	0.5514	0.547	2.61
7	8.388	8.578	8.696	7.4572	7.493	12.14
8	20.74	21.07	21.08	21.0364	21.159	13.36
9	19.69	20.96	21.08	21.5284	21.556	20.49
10	0.100	0.100	0.186	0.1000	0.100	0.24
Weight(lb)	5089	5076.85	5084.9	5060.85	5061.03	4784.29

CHAPTER 4

CASE STUDIES FOR MODEL UPDATING

4.1. Obtaining of Modal Parameters by experimental method

In general, a number of information can be obtained about the dynamic properties of the structures through the numerical modeling of the structures. Within the scope of the thesis study, a structural experiment model was created at Erciyes University Civil Engineering Laboratory and dynamic parameters were determined by Structural Health Monitoring methods. By means of the accelerometers used, the dynamic data at the time of vibration are recorded. The method used here is an output-output method in which it is almost impossible to use another method when collecting dynamic data of existing structures. Because, while using this method, it is not necessary to know the forces that make up the vibration and other dynamic characteristics of the structure. The following sensor used in the experimental work is MEMS-based and has the ability to display data at 1000 Hz and transmit data wirelessly.

Figure 4.1. A view of the sensors used in experimental studies

4.2. Case A

In the experimental study in which the Structural Health Monitoring system was modeled, pipe section members were used and they were connected to each other by means of sphere joints. It can be modeled in different types of structures thanks to this system which is frequently used for passing high openings. The materials and cross-sectional features used in the experiment are shown in the table below.

Table 4.1. Properties of the material used in the experiment

Section Properties		Material Properties	
Area (mm2)	399,73	**E (GPa)**	190
I (mm4)	77.111,85	**Density (kg/m3)**	7700
J (mm4)	154.223,7	**J (poisson ratio)**	0,3

Using the above-mentioned cross-section and material, the structural model shown in the following figure was created.

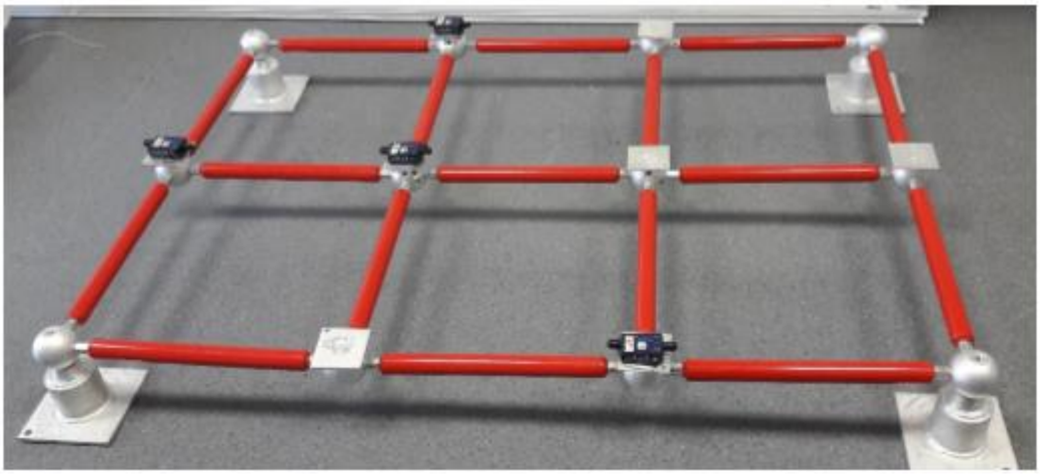

Figure 4.2. Example experimental setup for Structural Health Monitoring Case A

An example of the experimental setup and sensors used to test the structural health monitoring application is shown in the following figure.

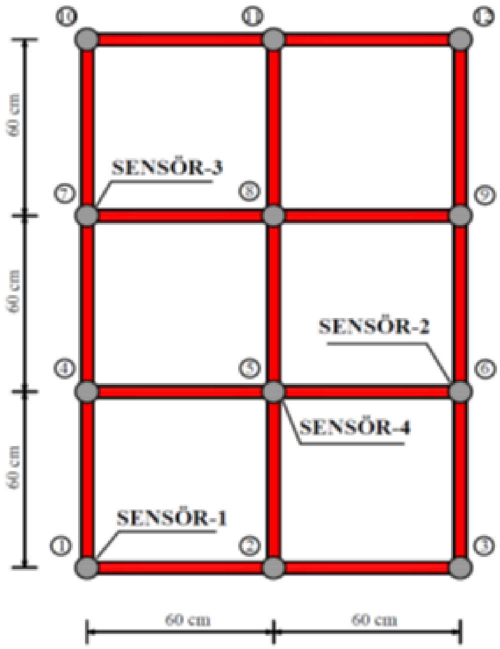

Figure 4.3. Sample sensor layout from the experiment

Four intelligent wireless accelerometers were used to record data generated during free vibration by exposure to vibration. One of these accelerometers is regarded as a reference accelerometer and the other sensors are placed at all the nodes.

In Table 4.3., the values of the modes corresponding to the natural frequencies are given.

Table 4.2. Natural Frequencies by experimental analysis of Case A

No.	Natural Frequencies (Hz)
1	35.81
2	50.25
3	56.54
4	60.69
5	81.08
6	88.77
7	116.59
8	156.16

Table 4.3. Modes by experimental analysis of Case A

w (Hz) \ No	35.81	50.25	56.54	60.69	81.08	88.77	116.59	156.16
1	0.9890	1.0000	1.0000	-0.2498	-0.3032	0.0029	-0.2038	0.1197
2	0.8171	0.1132	-0.8500	-0.7142	0.9715	-0.9756	-0.2348	0.1772
3	1.0000	0.2721	-0.1111	0.0954	0.5715	-0.0073	1.0000	-0.9994
4	0.7650	0.0979	-0.3171	1.0000	1.0000	0.9347	-0.2479	0.1964
5	0.8068	-0.0890	-0.8585	-0.7255	-0.9831	1.0000	-0.1974	-0.1677
6	0.9997	-0.2770	-0.0998	0.1120	-0.5679	-0.0756	0.9915	1.0000
7	0.7778	-0.1290	-0.3098	0.9940	-0.9886	-0.8960	-0.2808	-0.2069
8	0.9854	-0.9883	0.9935	-0.3030	0.3049	0.0305	-0.2038	-0.1207

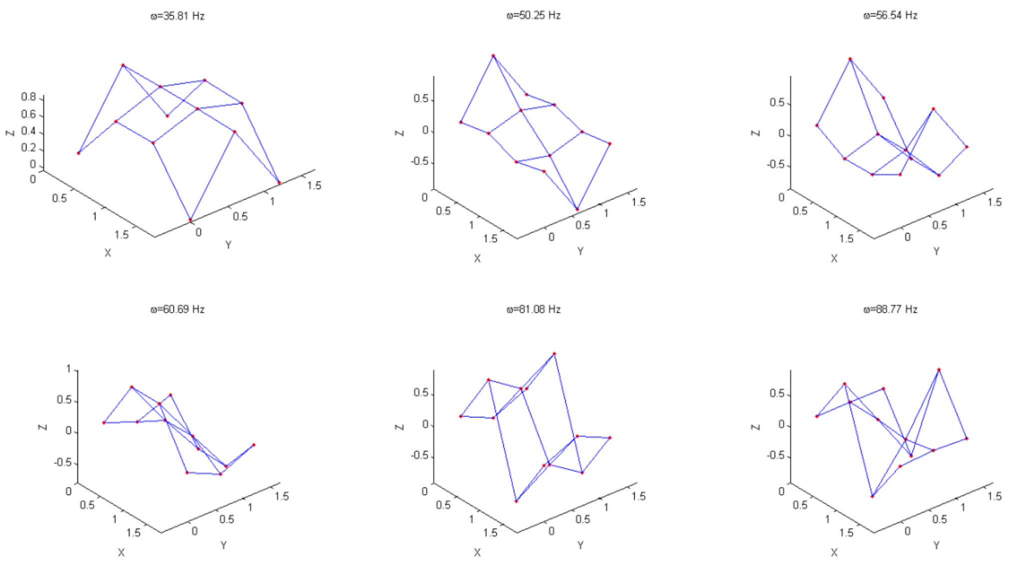

Figure 4.4. Mode shapes by experimental analysis of Case A

The dynamic parameters are investigated by obtaining mode shapes and natural frequencies according to the analysis and test results. The obtained parameters can be compared with the dynamic parameters to be obtained by the current model of the structure, and it can be decided whether or not the numerical model of the structure is defined correctly. At the same time, the numerical model of the structure can be updated using experimentally obtained parameters. If there is any damage to the structure, this can be determined by checking with experimental parameters. There are various methods for updating the current numerical model of the structure and for determining the damage. Accurate determination of the dynamic parameters to be obtained as a result of the experiment is very important for model updating and damage detection. Dynamic parameters can be obtained by following the dynamic behaviors of structures with intelligent wireless sensors used in Structural Health Monitoring which is becoming widespread nowadays.

4.3 Numerical Analysis for Test Structure Case A

A finite element model consisting of Euler-Bernoulli beam elements located in the X-Y plane was used as analytical representation of structure. The model consist of 12 nodes, and 17 beam elements. The coordinates are shown in table 4.4. Each node on the structure was considered to have 6 degrees of freedom (DOF). Apart from the global rotation around the x-axis, all the extreme corners of the grid are assumed to be constrained in all DOF. This results the total DOF being 52, from which only those corresponding to the global dz are measured for model updating. Material properties and section properties are shown in table 4.5.

Table 4.4. Node Coordinates for Test Structure Case A

No	**X(cm)**	**Y(cm)**
1	0	0
2	60	0
3	120	0
4	0	60
5	60	60
6	120	60
7	0	120
8	60	120
9	120	120
10	0	180
11	60	180
12	120	180

Table 4.5. Properties of the material used in the numerical analysis Case A.

Section Properties		**Material Properties**	
Area (mm2)	399,73	**E (GPa)**	190
I (mm4)	77.111,85	**Density (kg/m3)**	7700
J (mm4)	154.223,7	**J (poisson ratio)**	0,3

Table 4.6. Natural Frequencies for Numerical Analysis for Case A

No.	Natural Frequencies (Hz)
1	36.61
2	52.43
3	59.84
4	62.82
5	84.79
6	93.09
7	118.59
8	156.96

Table 4.7. Modes for Numerical Analysis Case A.

w (Hz) No	**36.61**	**52.43**	**59.84**	**62.82**	**84.79**	**93.09**	**118.59**	**156.96**
1	0.9822	1.0000	1.0000	0.0000	-0.3448	0.0000	-0.2384	-0.1416
2	0.7802	0.1174	-0.5931	-1.0000	1.0000	1.0000	-0.2570	-0.2112
3	1.0000	0.3019	-0.1014	0.0000	0.5858	0.0000	1.0000	1.0000
4	0.7802	0.1174	-0.5931	1.0000	1.0000	-1.0000	-0.2570	-0.2112
5	0.7802	-0.1174	-0.5931	-1.0000	-1.0000	-1.0000	-0.2570	0.2112
6	1.0000	-0.3019	-0.1014	0.0000	-0.5858	0.0000	1.0000	-1.0000
7	0.7802	-0.1174	-0.5931	1.0000	-1.0000	1.0000	-0.2570	0.2112
8	0.9822	-1.0000	1.0000	0.0000	0.3448	0.0000	-0.2384	0.1416

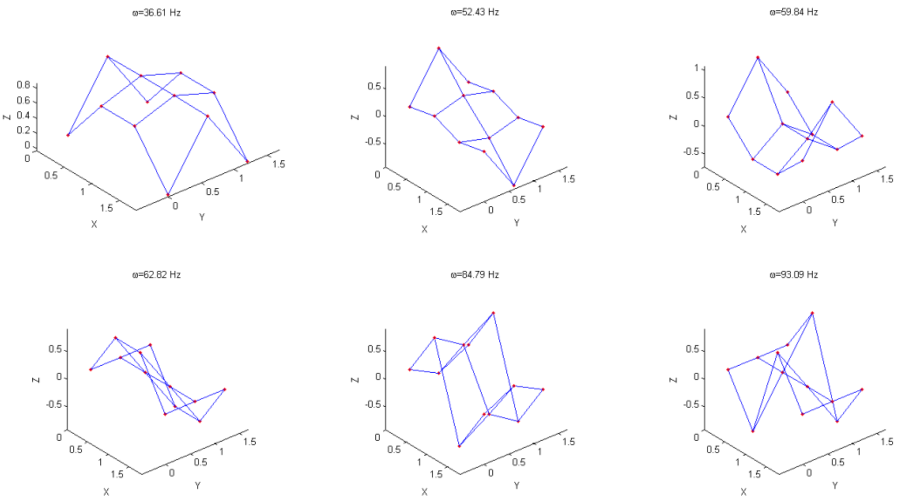

Figure 4.5. Mode shapes for the numerical analysis

Table 4.8. Modes for Updated Model with 17 parameters

w (Hz) \ No	**35.81**	**50.26**	**57.06**	**62.43**	**80.04**	**88.56**	**115.90**	**156.18**
1	0.9977	1.0000	0.9694	-0.1223	0.2987	-0.0121	-0.2108	0.1248
2	0.8063	0.1101	-0.6904	-0.8315	-0.9927	-0.8886	-0.2694	0.1984
3	0.9994	0.2510	-0.1624	0.0640	-0.5419	0.0301	1.0000	-0.9957
4	0.7594	0.0972	-0.4321	0.9874	-0.8825	1.0000	-0.2753	0.2086
5	0.7976	-0.1076	-0.6919	-0.8400	1.0000	0.8990	-0.2433	-0.1933
6	1.0000	-0.2593	-0.1505	0.0811	0.5279	-0.0788	0.9947	1.0000
7	0.7780	-0.1278	-0.4300	1.0000	0.8708	-0.9670	-0.2951	-0.2148
8	0.9903	-0.9788	1.0000	-0.1610	-0.2956	0.0321	-0.2116	-0.1262

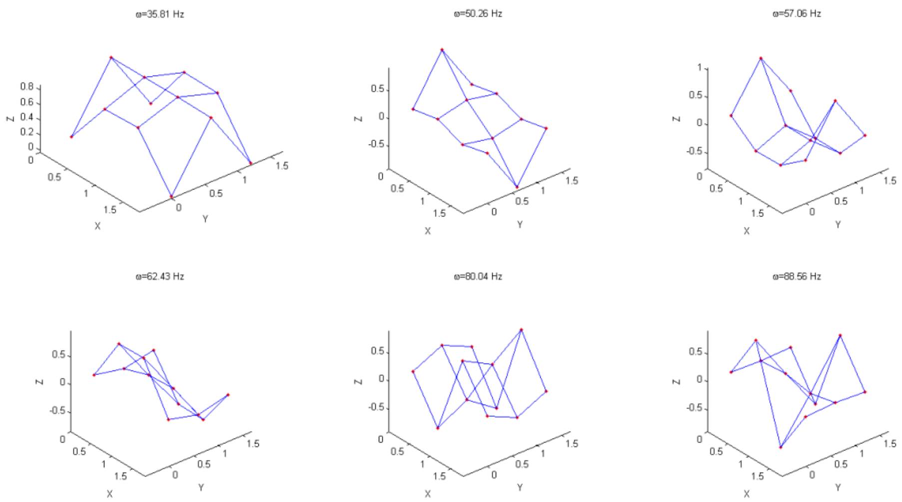

Figure 4.6. Mode shapes for updated model with 17 parameters,

Table 4.9. Modes for Updated Model with 2 parameters

w (Hz) \ No	**35.51**	**51.17**	**58.07**	**61.23**	**81.03**	**89.75**	**116.39**	**152.68**
1	0.9430	1.0000	1.0000	0.0000	-0.3645	0.0000	-0.2268	-0.1380
2	0.8087	0.1264	-0.5508	-1.0000	1.0000	1.0000	-0.2613	-0.2156
3	1.0000	0.3021	-0.0986	0.0000	0.6027	0.0000	1.0000	1.0000
4	0.8087	0.1264	-0.5508	1.0000	1.0000	-1.0000	-0.2613	-0.2156
5	0.8087	-0.1264	-0.5508	-1.0000	-1.0000	-1.0000	-0.2613	0.2156
6	1.0000	-0.3021	-0.0986	0.0000	-0.6027	0.0000	1.0000	-1.0000
7	0.8087	-0.1264	-0.5508	1.0000	-1.0000	1.0000	-0.2613	0.2156
8	0.9430	-1.0000	1.0000	0.0000	0.3645	0.0000	-0.2268	0.1380

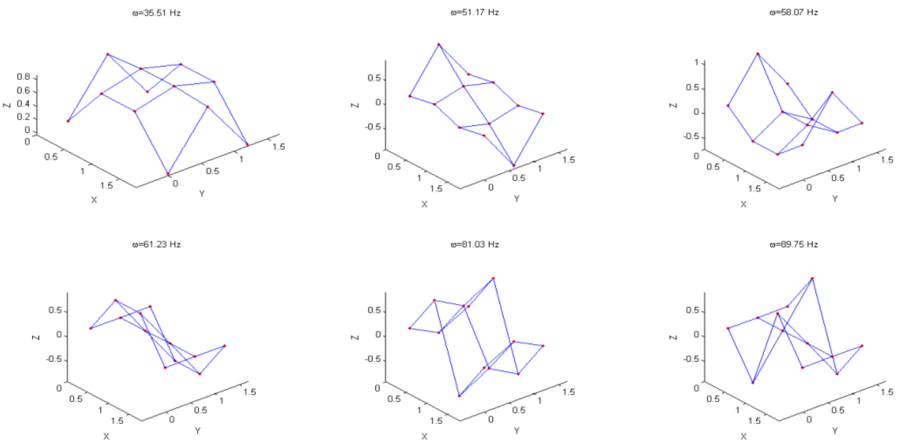

Figure 4.7. Mode shapes for Updated Model with 2 parameters

4.4. Case B

A finite element model consisting of elements located in the X-Y-Z plane was used for experimental and analytical representation of structure. The model consist of 20 nodes, and 41 elements. Each node on the structure was considered to have 6 degrees of freedom (DOF). Apart from the global rotation around the x-axis, all the extreme corners of the grid are assumed to be constrained in all DOF. This results the total DOF being 112. For this case no experimental analysis in the form of sensors to measure modal data wasn't used instead the data were made up with the help of the stochastic optimization code. Since it has 41 elements which will results in many results to be tabulated, only the mode shapes of the experimental and numerical analysis are shown in figure 4.10 and 4.11. The updated mode shapes are shown in figure 4.12, 4.13, 4.14 and 4.15 for the first, second third and fourth solutions respectively for three parameters consideration and figure 4.16 and 4.17 were for 41 parameters consideration. Material properties and section properties are shown in table 4.8.

Figure 4.8. Set up for Structure of Case B

Section Properties		Material Properties	
Area (mm2)	399,73	**E (GPa)**	190
I (mm4)	77.111,85	**Density (kg/m3)**	7700
J (mm4)	154.223,7	**J (poisson ratio)**	0,3

Table 4.10. Material properties and section properties

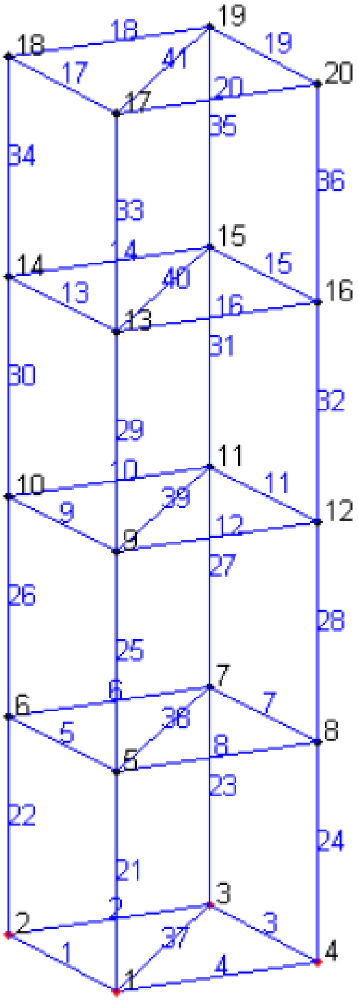

Figure 4.9. Structure layout from the experiment

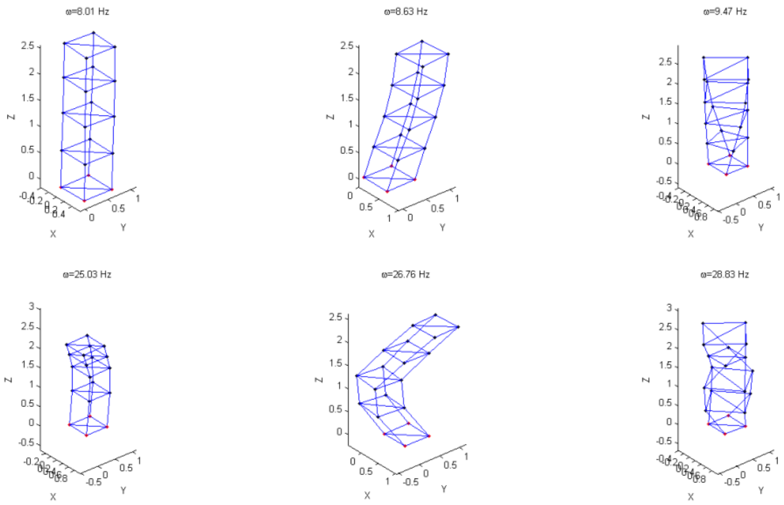

Figure 4.10. Mode shapes for experimental analysis

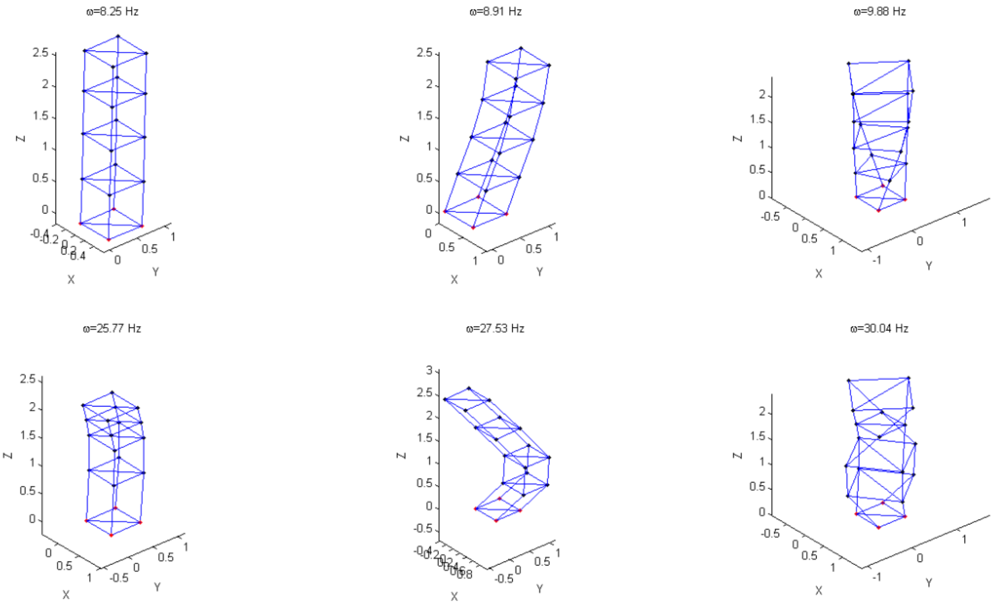

Figure 4.11. Mode shapes for numerical analysis

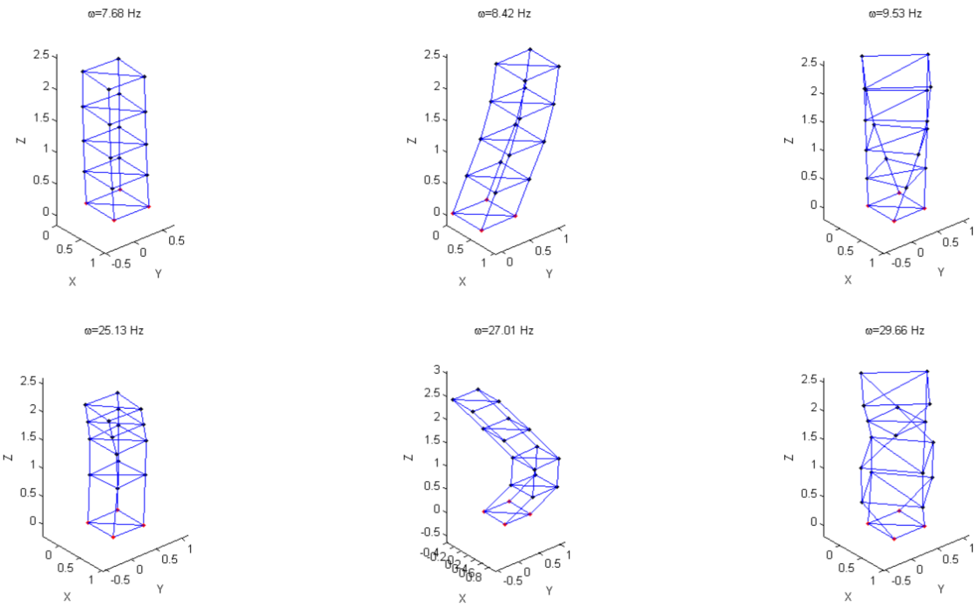

Figure 4.12. Updated mode shapes with 3 parameters (solution 1)

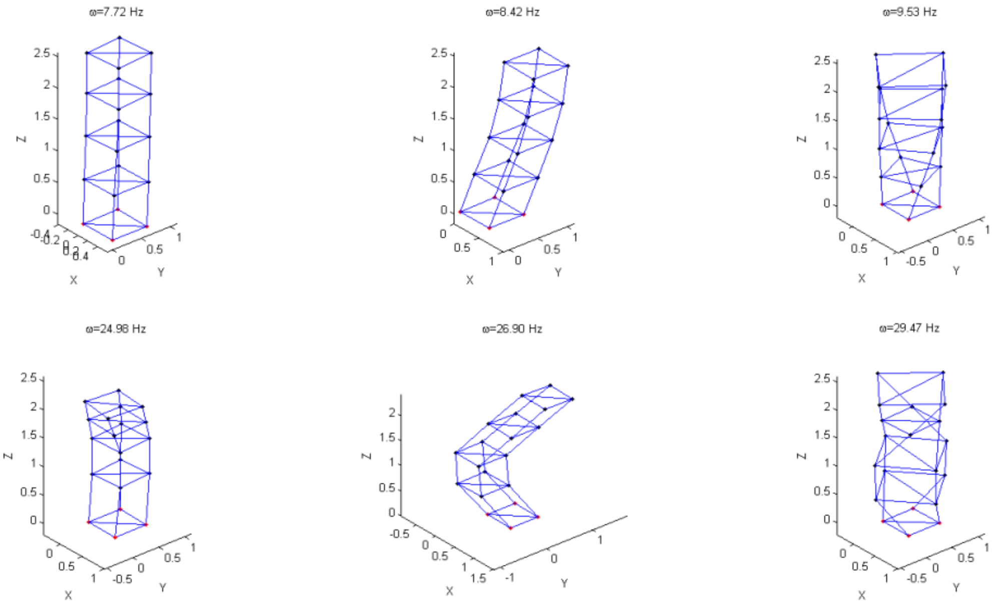

Figure 4.13. Updated mode shapes with 3 parameters (solution 2)

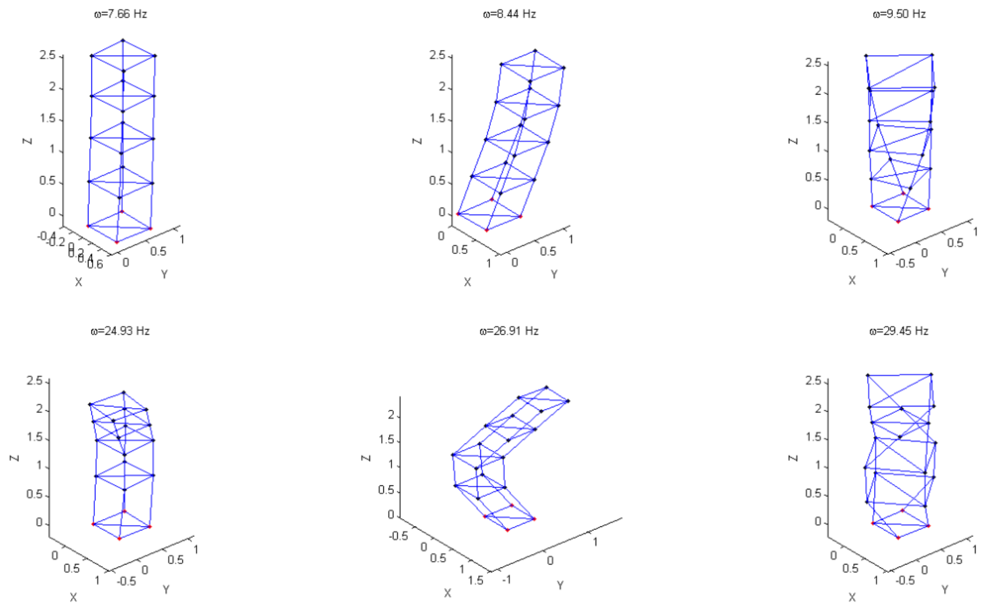

Figure 4.14. Updated mode shapes with 3 parameters (solution 3)

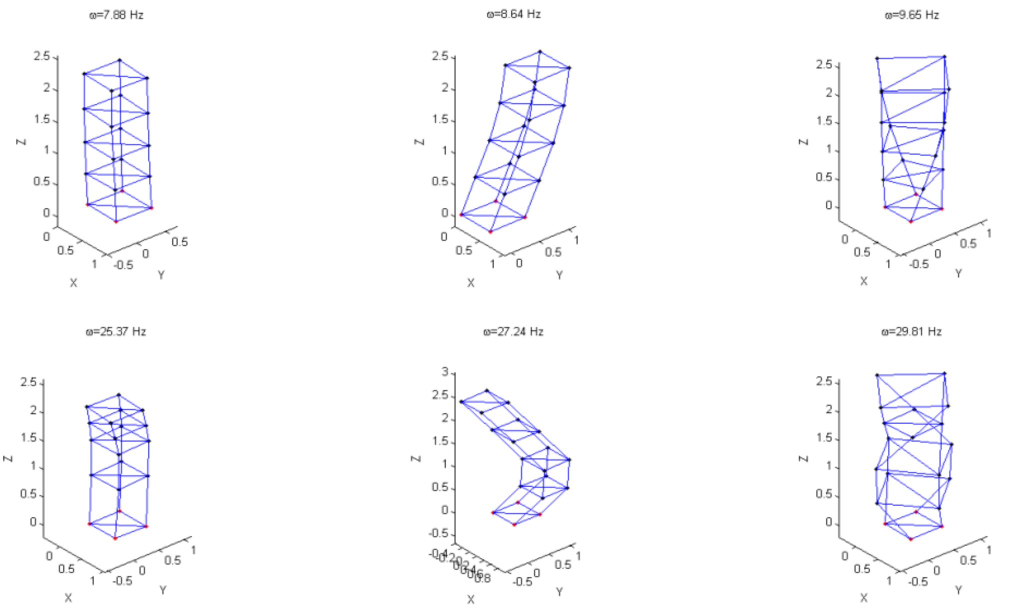

Figure 4.15. Updated mode shapes with 3 parameters (solution 4)

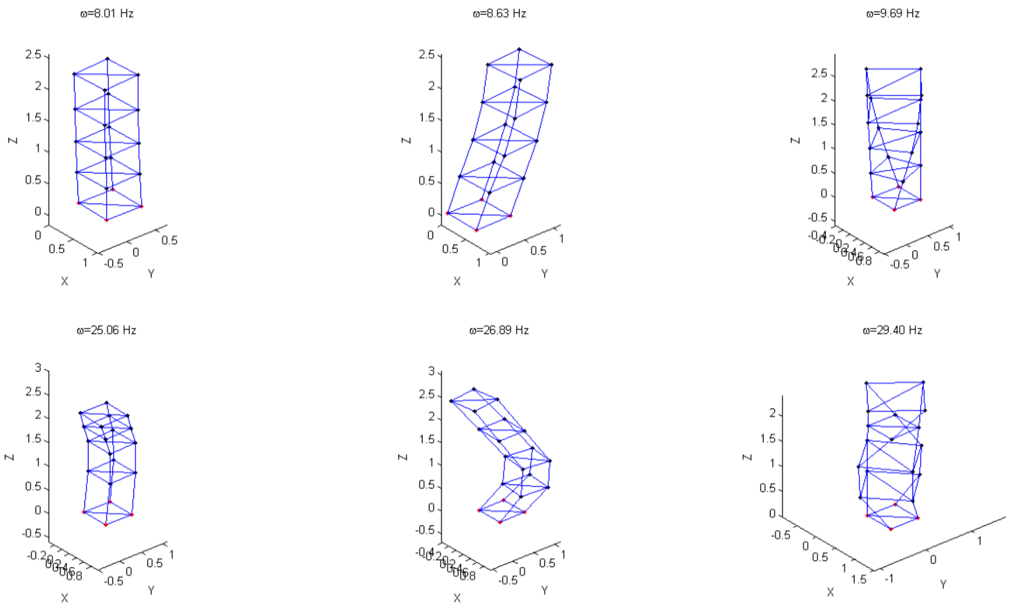

Figure 4.16. Updated mode shapes with 41 parameters (solution 1)

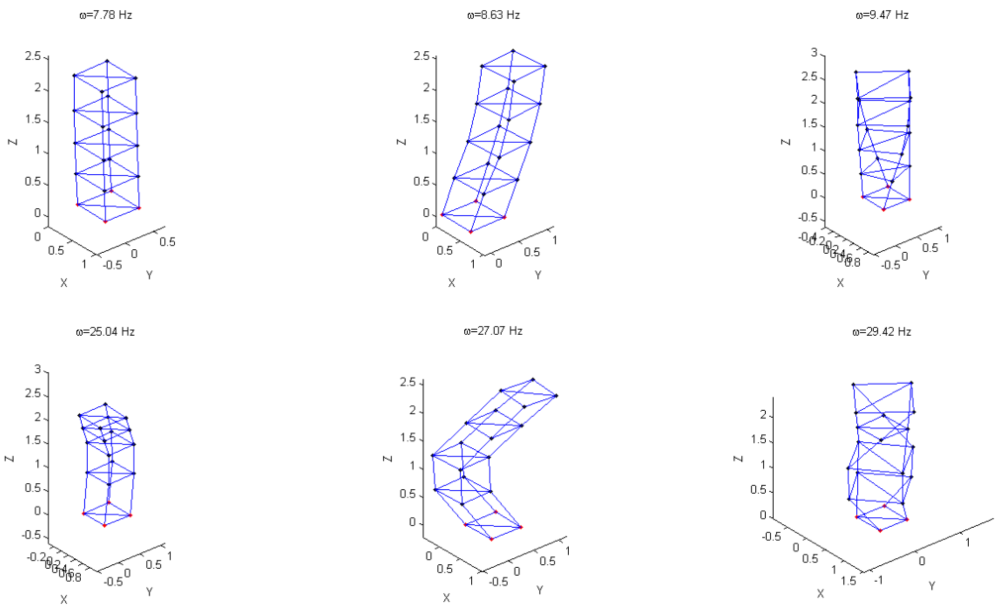

Figure 4.17. Updated mode shapes with 41 parameters (solution 2)

CHAPTER 5

DISCUSSIONS AND CONCLUSIONS

5.1. Discussions

The Crowned Cross and the Gaussian test functions were used to show how effective the stochastic optimization code is. The results obtain for the Crowned Cross function shows a global optimum of 2.0626 for xi = ±1.349406608602084 for i=1,2 which shows the way this method is effective in finding global optimum. The results for Gaussian function equally shows how effective the algorithm works. The 10-Bar Truss is used to demonstrate the application of stochastic optimization code to obtain optimal design of truss structures that are under stress and deflection constraints. Evaluation of the performance of the stochastic optimization code is done using the well-known 10-Bar Truss benchmark problem. Three different optimization runs were made with the population size kept at 500 but groups of 20,30 and 40 were created and the results of which are shown in Tables 3.3, 3.4 and 3.5. The increment in the number of groups didn't have that much of a significance on the overall weight of the structure obtained as shown on Tables 3.3, 3.4 and 3.5.The population with 30 groups yielded better results than the other two. The numerical results demonstrated how efficient and the capabilities of the Stochastic optimization code in evaluating the optimal designs for truss structures. The results that were obtained using the stochastic optimization code was compared with results obtained with other methods. The Stochastic Optimization code obtained better results when compared to the other methods. In table3.6,there is some difference in the member areas between the results obtained from other methods and the Stochastic Optimization code which is due to the fact that the method used in this thesis provides us with more than one global solution. It tries to find set of optimal solution instead of one or best optimal solution. Chapter 4 dealt with model updating conducted on the pipe section members which were connected to each other by means of sphere joints. The proposed stochastic method used in this thesis was tested using a numerical example and an experimental structure(pipe section members) by which the frequencies obtained by using sensors was compared with the numerical ones predicted using the proposed stochastic optimization code and the model updated. In Table 4.8 and 4.9 the updated modes and frequency are shown for 17 and 2 parameters respectively for the model updating of Case A. High computational time is one of the challenges that comes with model updating using the proposed stochastic method because it searches for multiple solutions.

5.2 Conclusions

The stochastic optimization algorithm used in this work has demonstrated its effectiveness in solving optimization problems. The results that were obtained for the 10 bar truss, the Gaussian and the Crowned Cross test objective functions are a testimony to this. The model updating shows satisfactory results when matching the numerical and experimental results and also the updated models. With the stochastic optimization used in this work showing great effectiveness in solving optimization and model updating problems, further works will be done to improve the algorithm to solve more challenging problems and it improve its computation time.

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