

**OPTIMIZATION OF DOUBLE LAYER GRID STRUCTURES
USING FEM, SPSA AND NEURAL NETWORKS**

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SPSA AND NEURAL NETWORKS**

by

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Doctor of Philosophy**

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PENGOPTIMUMAN STRUKTUR GRID DWI-LAPIS DENGAN MENGUNAKAN FEM, SPSA DAN RANGKAIAN NEURAL

ABSTRAK

Pengoptimuman struktur grid dwi-lapis segiempat sama-atas-segiempat sama adalah berfaedah untuk tujuan rekabentuk. Untuk tujuan ini, kegunaan algoritma pengoptimuman yang berdasarkan kecerunan dengan ciri stokastik yang dikenali sebagai “static perturbation stochastic approximation optimization” (SPSA) belum diselidiki. Satu set langkah pengiraan untuk pengoptimuman terkekang ke atas struktur grid dwi-lapis segiempat sama-atas-segiempat sama dengan menggabungkan FEM, algoritma SPSA dan rangkaian neural telah dicadangkan. Sejumlah 208 set pengoptimuman telah dijalankan ke atas model struktur grid dwi-lapis segiempat sama-atas-segiempat sama dengan berbagai gabungan rentang $L(25m\sim75m)$ dan kedalaman $h(0.035L\sim0.095L)$. Daripada jumlah 208 set data, sejumlah 173 dan 35 telah digunakan untuk melatih dan menguji rangkaian neural “radial basis function”(RBF) dan “generalized regression”(GR) untuk ramalan rekabentuk optima dan pesongan maksima struktur grid dwi-lapis dengan berlainan rentang dan kedalaman struktur grid. Keputusan ujian menunjukkan bahawa rangkain neural RBF dan GR yang terhasil berupaya meramal rekabentuk optima dan pesongan maksima dengan ralat purata maksima 5.0166% untuk ramalan rekabentuk optima dan 1.6675% untuk ramalan pesongan maksima. Rangkaian neural GR telah didapati menunjukkan prestasi umum yang lebih baik daripada rangkaian neural RBF di mana ralat ramalan purata masing-masing adalah 3.0185% berbanding 5.0166% untuk kes rekabentuk optima dan 0.4641% berbanding 1.6675% untuk kes pesongan maksima. Jumlah relatif data yang kecil, iaitu 173 untuk latihan dan 35 untuk ujian prestasi,

yang digunakan dalam kajian ini telah menunjukkan bahawa kaedah yang dicadangkan yang melibatkan gabungan FEM, SPSA adalah satu kaedah yang berkesan dalam penjanaan data yang boleh dipercayai untuk membentuk rangkaian neural RBF dan GR untuk kegunaan sebagai satu alatbantu praktikal untuk tujuan ramalan rekabentuk optima dan pesongan maksima struktur grid dwi-lapis segiempat sama-atas-segiempat sama.

OPTIMIZATION OF DOUBLE LAYER GRID STRUCTURES USING FEM, SPSA AND NEURAL NETWORKS

ABSTRACT

Optimization of square-on-square double layer grids is beneficial for design purpose. For this purpose, use of a gradient based optimization algorithm incorporating stochastic feature called static perturbation stochastic approximation (SPSA) has not investigated. A computational procedure for constrained optimization of square-on-square double layer grids combining FEM, SPSA algorithm and neural network has been formulated. Using the formulated procedures, a total of 208 set of optimization have been carried out on square-on-square double layer grids with different combinations of span L (25m~75m) and height h ($0.035L \sim 0.095L$). Of the 208 sets of data, 173 and 35 have been used in the training and testing of radial basis function(RBF) and generalized regression(GR) neural networks for prediction of optimal design and the corresponding maximum deflection of square-on-square double layer grids with different spans and heights. Testing results obtained have demonstrated that both RBF and GR neural network models have been shown to be able to predict optimal design and maximum deflection of square-on-square double layer grids with maximum average error of only 5.0166% for optimal design and 1.6675% for maximum deflection. GR neural network model has been found to show better performance generality than RBF neural network model where the corresponding average prediction errors are 3.0185% versus 5.0166% for optimal design and 0.4641% versus 1.6675% for maximum deflection. Relatively small number of 173 training data and 35 testing data used in this study have shown that

the proposed methodology of combining FEM, SPSA algorithm is effective for the purpose of generation of reliable data to train GR and RBF neural network models for use as a practical tool for the prediction of optimal design and maximum deflection of square-on-square double layer grids.

CHAPTER 1

INTRODUCTION

1.1 Introduction

The term 'space structure' refers to a structural system where structural members are so oriented that they lie in three dimensional spaces. This is in contrast to a 'plane structure' where no more than two dimensions are involved. In the case of a plane structure, the external loads as well as the internal forces are in a single plane. This is the plane that also contains the (idealized) structure itself, both in its initial unloaded state and in its deformed loaded state. In the case of a space structure, the combination of the configuration, external loads, internal forces and displacements of the structure extends beyond a single plane.

In practice, the term 'space structure' is used to refer to a number of families of structures that include grids, barrel vaults, domes, towers, cable nets, membrane systems, foldable assemblies and tensegrity forms. Space structures cover an enormous range of shapes and are constructed using different materials such as steel, aluminum, timber, concrete, fiber-reinforced composites, or a combination of these. It is noted that the term 'spatial structure' is sometimes used instead of space structure. The two terms are considered to be synonymous.

Space structures are economical and aesthetically pleasing in appearance. They provide a unique solution for covering large column free areas. A growing interest in space structures has been witnessed worldwide over the last half century. The search

for new structural forms to accommodate large unobstructed areas desired by architects has always been the main objective of engineers. With the advent of new building techniques and construction materials, space structures frequently provide the right answer and satisfy the requirements for lightness, economy, and speedy construction. Significant progress has been made in the process of the development of space structures. A large amount of theoretical and experimental research programs have been carried out by many researchers all over the world.

In terms of distribution of members and materials, space structures may be divided into three categories:

- i. lattice space structures that consist of discrete and normally elongated elements
- ii. continuous space structures that consist of components such as slabs, shells, membranes,
- iii. Biform space structures that consist of a combination of discrete and continuous parts.

In the past few decades, the proliferation of the different categories of space structure as pointed above was mainly due to its great structural potential and visual beauty. New and imaginative applications of space structures are being demonstrated in a wide range of building types for a variety purposes such as sports arenas, exhibition pavilions, gymnasiums, cultural centers, auditoriums, shopping malls, assembly halls, transportation terminals, airplane hangars, workshops, warehouses, leisure centers, transmission towers, radio telescopes and many other purposes. Space

structures have been used not only on long-span roofs, but also on mid- and short-span enclosures as roofs, floors, exterior walls, and canopies.

There are some important factors influencing the rapid development of the application of space structures as mentioned above. First, the search for large indoor space has always been the focus of human activities. Consequently, sports tournaments, cultural performances, mass assemblies, and exhibitions can be held under one roof. The modern production and the needs of greater operational efficiency also created demand for large space with a minimum interference from internal supports. The space structure provides the benefit that the interior space can be used in a variety of ways. Thus it is ideally suited for such requirements.

As pointed out earlier, space structures can be classified as discrete, continuous or combination of discrete-continuous types. The focus of this study is on discrete type space structure. Examples of discrete structures which consist of frame, truss and grid structure are shown in Figure 1.1.

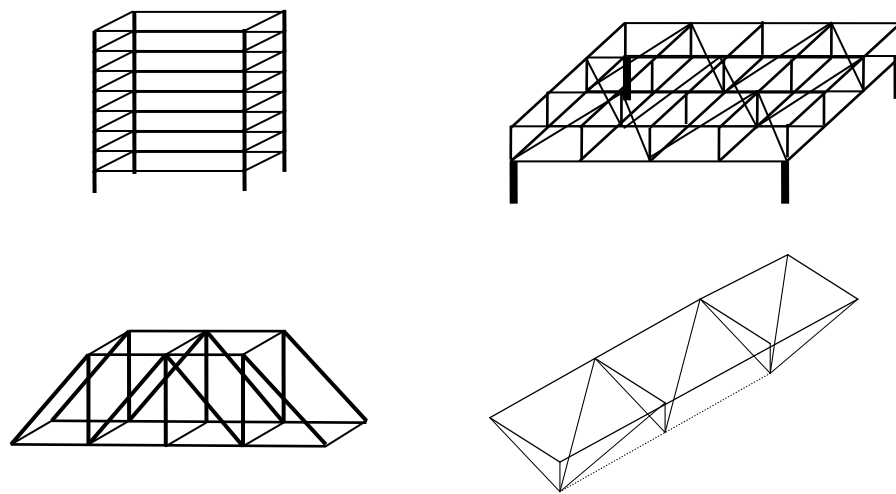


Figure 1.1: Examples of discrete-type space structures

1.2 Grid Structures

Double layer grid structure which is the focus of this study falls within the category of lattice space structures or discrete type structure as mentioned earlier. Space structures within this category are made up of many number of discrete straight members connected at joints (which could be of pinned, rigid or semi-rigid types) to form structures with a variety of forms. Some important types of lattice structures are described in the section.

According to Makowski(1981), a grid can be defined as a structural system involving one or more planar layers of elements. A single layer grid, or flat grid, consists of a planar arrangement of rigidly connected beam elements. The external loading system for a flat grid consists of forces perpendicular to the plane of the grid and/or moments whose axes lie in the plane of the grid. The reason for classification of a flat

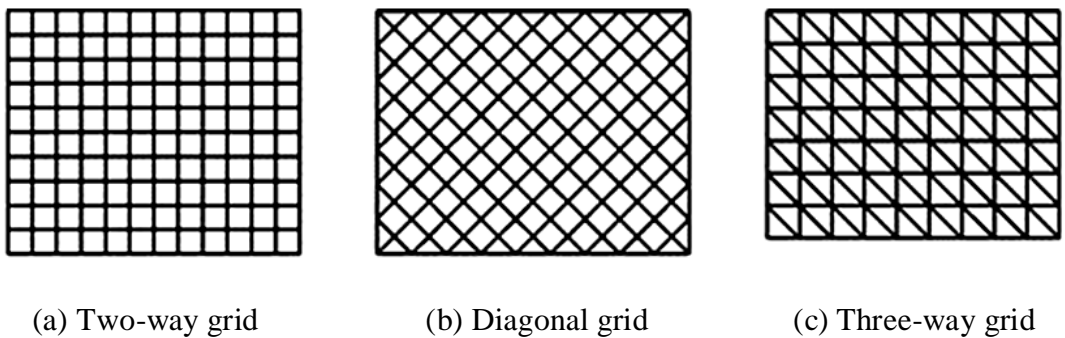


Figure 1.2: Some basic grid patterns [Nooshin et al(1993)]

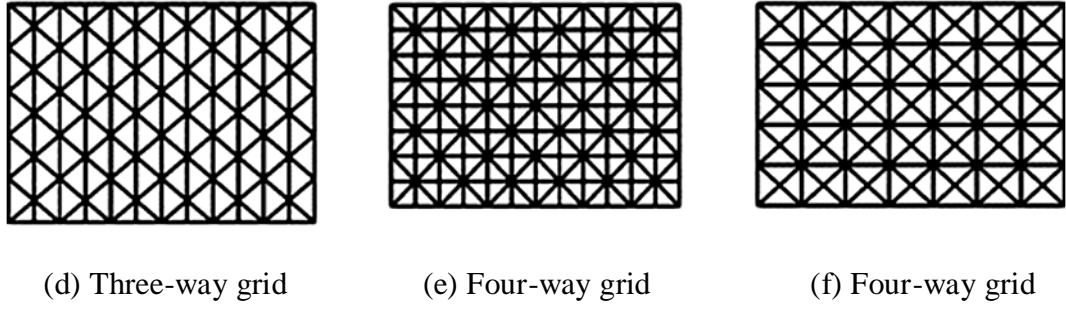
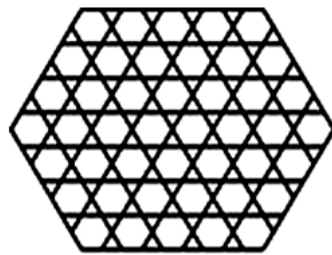
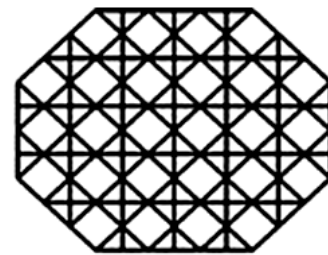


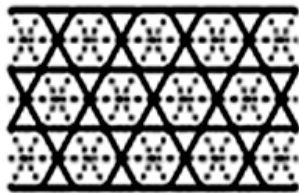
Figure 1.2: Continued



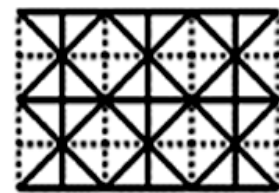
(a) A Grid derived from
a three-way pattern



(b) A Grid derived from
a four-way pattern



(c) Removal of dotted lines
gives rise to the pattern
of the grid above



(d) Removal of dotted lines
gives rise to the pattern
of the grid above

Figure 1.3: Pattern creation by element removal [Nooshin et al(1993)]

grid as a space structure is that its external loads and displacements do not lie in the plane that contains its (idealized) configuration. A number of basic grid patterns are illustrated in Figure 1.2. The 'two-way' pattern, shown in Figure 1.2(a), is the simplest pattern for a flat grid. It consists of two sets of interconnected beams that run parallel to the boundary lines. The diagonal pattern, shown in Figure 1.2(b), consists of two parallel sets of interconnected beams that are disposed obliquely with

respect to the boundary lines. Figures 1.2(c)-(f) show some basic three-way and four-way grid patterns. The basic grid patterns of Figure 1.2 are frequently used in practice.

However, there are also many other grid patterns that are commonly used. These patterns are normally derived by removal of some elements from the basic patterns of Figure 1.2. Two examples of this type of operation are shown in Figure 1.3. The grid pattern in Figure 1.3(a) is obtained from a three-way pattern by omitting every other beam line. This is illustrated in Figure 1.3(c), showing apart of the grid of Figure 1.3(a) with the beam lines shown by dotted lines. The grid of Figure 1.3(b) is obtained from a four-way pattern by removal of a number of beam lines as indicated in Figure 1.3(d). As the different grid patterns do indeed have their own characteristics, in designing a grid configuration, to find the most suitable pattern for the particular application the following points should be considered. There are no inherent good or bad grid patterns and the suitability of a pattern for each particular case should be considered with regard to the shape and size of the boundary, support positions, loading characteristics, material to be used and the manner in which the structure is to be constructed. These points also apply in relation to all other space structure forms.

1.2.1 Double Layer Grids

A double layer grid consists of two (nominally) parallel layers of elements that are interconnected together with web elements[Makowski(1981)]. Views of some commonly used patterns of double layer grids are shown in Figure 1.4. In this figure, the top layer elements are shown by thick lines and the bottom layer elements as well

as the web elements are shown by thin lines. The double layer grid of Figure 1.4(a) consists of a two-way top layer and a two-way bottom layer. In the case of the grid of Figure 1.4 (b), both the top and bottom layers have a diagonal pattern. There are also many double layer grids built with a two-way pattern for one of the layers and a diagonal pattern for the other layer. A double layer grid of a different kind is shown in Figure 1.4(c). Here, the top and bottom layers are of an identical shape and are positioned such that their plan views are coincident. Also, in this case all the web elements lie in vertical planes. The result is a double layer grid that effectively consists of a number of intersecting plane trusses. A grid of this type is referred to as a truss grid. A truss grid may be regarded as a flat grid whose elements are trusses. A primary double layer grid pattern, such as the one shown in Figure 1.4(a), is

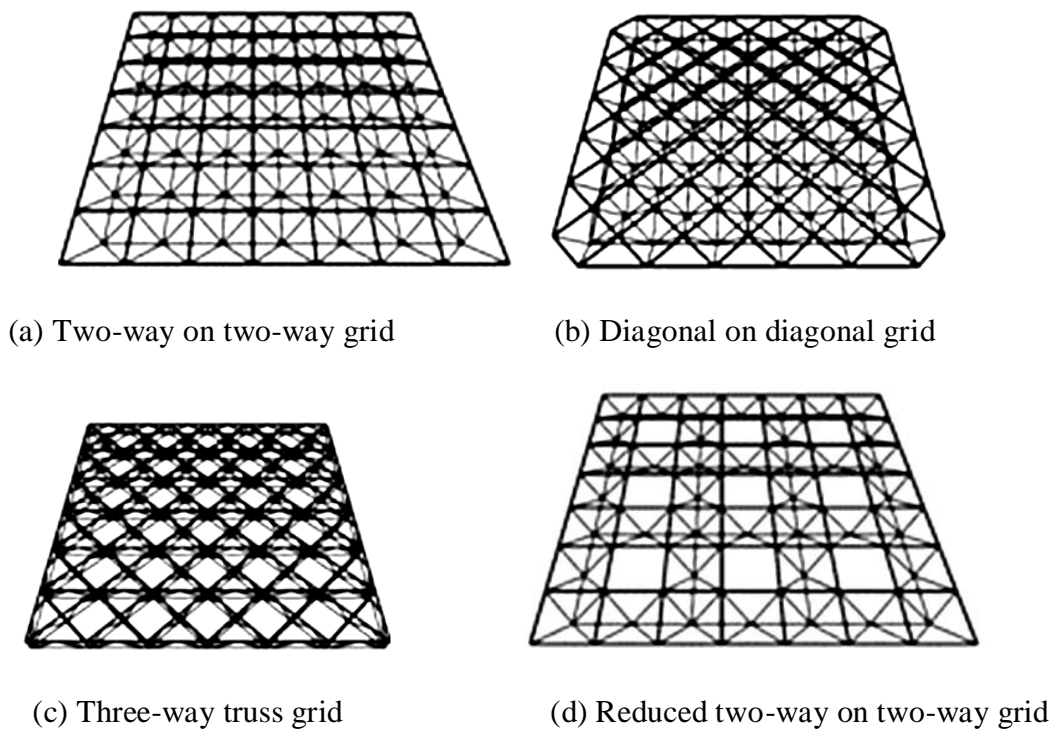
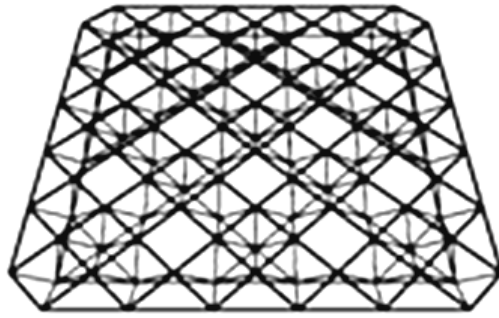
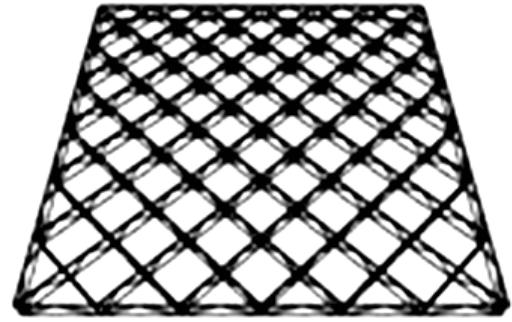


Figure 1.4: Examples of double layer grids [Nooshin et al(1993)]



(e) Reduced diagonal on diagonal grid



(f) Diagonal truss grid

Figure 1.4: continued

often used as a basis for the creation of various reduced forms by removing a number of elements. An example of this is shown in Figure 1.4(d). This grid is obtained from the grid of Figure 1.4(a) by removing the bottom layer and web elements that are connected to a number of bottom layer nodes. A similar process is used for obtaining the reduced grid of Figure 1.4(e) from the grid of Figure 1.4(b). Also, the diagonal truss grid of Figure 1.4(f) is obtained by removing the non-boundary third-direction trusses of the grid of Figure 1.4(c). Grids may also involve more than two layers of elements, allowing for greater structural depth to cater for longer spans. There is a fundamental difference between the structural behavior of flat grids and that of double layer (or multilayer) grids. Flat grids are bending dominated with the elements being under bending moments, shear forces and torques. In contrast, the main internal forces in the elements of double layer grids are axial forces. Bending moments, shear forces and torques are also present in the elements of double layer (or multilayer) grids in various proportions depending on the cross sectional properties of the elements and the jointing system. However, the non-axial force effects in these cases are normally secondary. In Figure 1.5, four selective double layer grids from all over the world are displayed.

The other types of space structures are barrel vaults and domes. Although they are not the focus of this study, brief explanation about them are given in the following section in order to differentiate between them and the double layer grids considered in this study.



(a)

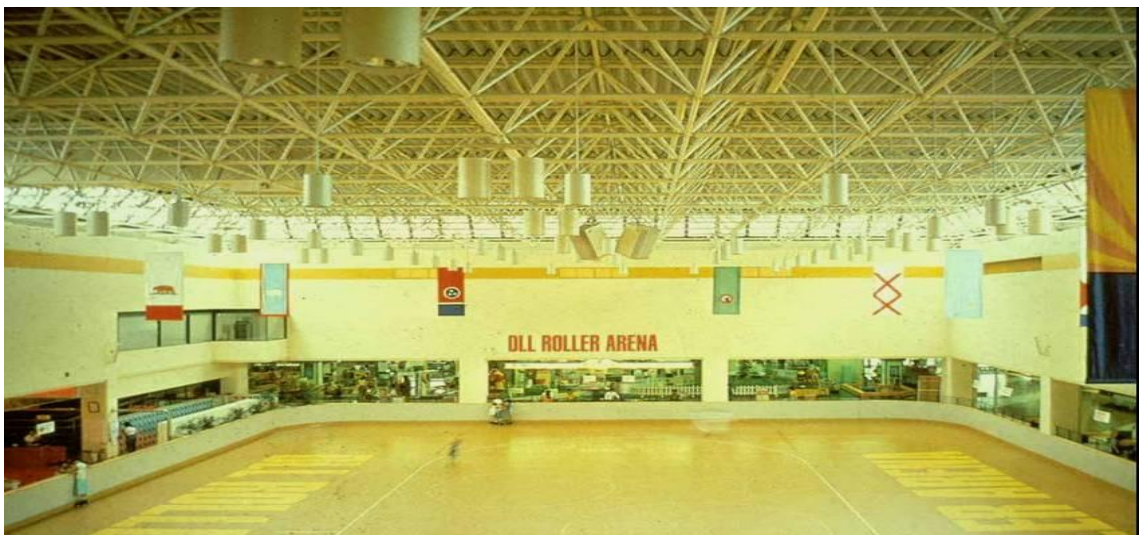


(b)

Figure 1.5: Selective double layer grids



(c)



(d)

Figure 1.5: continued

1.2.2 Barrel Vaults and Domes

A barrel vault is obtained by arching a grid along one direction[Makowski(1985)]. The result is a cylindrical form that may involve one, two or more layers of elements. Cross-sections of the barrel vaults can be circular, elliptic, parabolic or many other

shapes. A dome is a structural system that consists of one or more layers of elements that are arched in all directions[Makowski(1984)]. The surface of a dome may be a part of a single surface such as a sphere or a paraboloid, or it may consist of a patchwork of different surfaces. Also, there are a large number of double layer (and multilayer) dome patterns that may be obtained from the combinations of the basic patterns. Included in these are truss domes that consist of intersecting curved trusses. Some examples of barrel vault configurations and domes are shown in Appendix A.

1.3 Configuration Processing

Besides the mentioned examples of space structures as described in the previous sections, there are many other innovative shapes that are possible to be realized using lattice type space structures. In order to carry out analysis for any space structures for evaluation of structural behaviour or design, it is necessary to examine a number of possible shapes. As lattice type space structures such as double layer grids are made up of many number of members joined together, determination of pattern of arrangement of members to form different shapes is an integral part of the analysis of space structures. In the field of space structures, such “arrangement of parts” is called “configuration”. Examples of configurations in a structural analysis context are:

1. the collection of all the nodal points of a structure or any subset of these points,
2. the collection of all the elements of a structure or any subset of these elements, and

3. the collection of all the points of a structure that are under a particular kind of load.

Configurations of space structures are rather difficult to generate due to the large number of members. Configuration processing of space structure is a technically tedious and time consuming task. Configuration should be properly represented in a numerical model of space structures. In particular, when a computer is involved in representation of a configuration then the information stored in the computer about the configuration is bound to be in terms of some sort of numerical model. To carry out a configuration processing task, the computing system should be provided with information about the configuration to be created. This information should be provided through some numerical and/or graphic input together with instructions regarding the manner in which the input should be processed. These instructions may be supplied through menus and/or coded directives of various forms.

1.3.1 Formex Algebra

When dealing with space structures, the concepts of formex algebra provide a suitable medium for configuration processing[Nooshin(1984), Nooshin(1988)]. Formex algebra is a mathematical system that provides a convenient basis for solution of problem in data generation and computer graphics. A structural engineer or an architect who is concerned with the design of space structures is likely to encounter many different structural configurations. As one of the first steps in the analysis and design of a space structure, it is necessary to generate the data containing the information regarding the elements of the structure and the manner in which these are connected together. Formex algebra provides a convenient means

for achieving this purpose. In the case of formex configuration processing, a small part of the structure is explicitly represented and then operators and functions are used to generate information about the entire configuration. With a computing system incorporating suitable formex software, the mentioned process may be used to generate data describing the element connectivity and node coordinates.

1.3.2 Formian

Formian is the programming language invented and developed by Hoshyar Nooshin and his team in the Space Structures Research Centre at the University of Surrey in United Kingdom [Nooshin et al (1993)]. In this programming language the basic principles of formex algebra as mentioned earlier are applied. Formian makes possible to build numerical models of the designed form of any kind of the space structures. These numerical models are bases for various analyses, which have to be carried out during the process of the design. The mathematical formulations may use many times elements of symmetry and asymmetry. Very complex shapes of structural systems may be defined in this language by usage of very short form of description what is possible owing to application the basic rules of the symmetry. Even asymmetrical forms of some space structures can be easily and simply defined in Formian by suitable applying of symmetrical formulations. Formian has been applied in numerous research studies, e.g. Nooshin and Tomatsuri(1995), Nooshin(1996) and Nooshin et al(1997). Due to fact that Formian is the best tool for achieving this task, Formian is employed for configuration processing in this study.

1.4 Optimal Design of Space Structures

Due to the characteristic of load transfer through three dimensional action, space structures are very efficient structural systems to carry heavy loads as well as to cover wide span column free areas. As the number of structural elements of the space structures is usually very large, it is essential to evolve strategies for their optimal design. In general, optimal design of space structures can be classified into categories as shown in Figure 1.6.

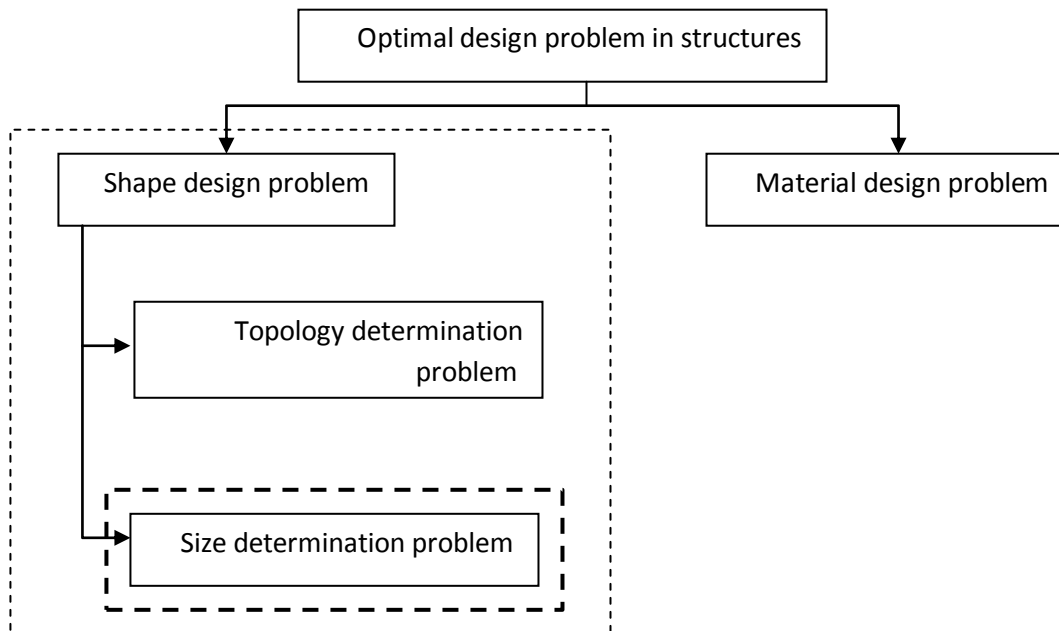


Figure 1.6: Classification of optimal design problem in structural engineering

In this study, shape design problem is considered. Under shape design problem, topology optimization deals with determination of arrangement of members while size determination problem deals with determination of cross-sectional area of members and length of members. Optimization problem considered in this study

belongs to the category of size determination problem under shape design problem. Only determination of cross-sectional area of member has been considered with the type of structure to be studied fixed.

Optimal design of space structures leads to structures with less weight and subsequently cost leading to structural systems which are very efficient in term of load carrying capacity to self-weight ratio. During the optimization process, critical structural responses such as maximum deflection and stress should not exceed the requirement stated in design codes. One of the most important requirements which should be checked in the design process of double layer grids is the maximum deflection checking. Due to the reason that large spans are covered without intermediate columns in this type of structures, design codes normally specify that the maximum deflection under serviceability condition should be limited. Optimal design of such large scale structures is very time consuming. Therefore to efficiently achieve the optimization task, it is necessary to reduce the computational time. In order to achieve such aim, an efficient analysis procedure where optimization can be carried out rapidly is an important factor to be considered. At the same time, the obtained solution should preferably be global minimum rather than local minimum. For that purpose, algorithm of optimization with feature of searching towards global is desired.

Optimization techniques can be divided into two main groups: gradient-based algorithms and evolutionary algorithms. The most time consuming part of the optimization process by the gradient-based algorithms lies in the sensitivity analysis phase. In contrast to this, the evolutionary algorithms do not need gradient

information. However, their stochastic nature causes a slow rate of convergence towards the global optimum. An effective algorithm with the features of both a gradient based and stochastic based approach is the so-called simultaneous perturbation stochastic approximation algorithm[Spall(1998)]. The essential feature of SPSA is the underlying gradient approximation that requires only two measurements of the objective function regardless of the dimension of the optimization problem. This feature allows for a significant reduction in computational time needed in optimization, especially in problems with a large number of variables to be optimized. Use of SPSA in optimization problem of large size has not been fully explored. With the use of SPSA, large number of structures with different input conditions can be optimized with lower computational cost.

From practical design point of view, the procedure of optimization using SPSA could then be further explored in the development of a tool for use as design aid. As structural design will generally involve repetitive analysis of structures of the same types but with different possible overall sizes, the developed tool for optimal design should be able to provide the optimal design with minimum input data. To this end, a tool which can provide prediction of optimal design with mere input of span and height is highly desirable. One of the powerful techniques that is able to provide rapid and accurate prediction of complex problems is artificial neural networks. Artificial neural network can also lead to reduction in computational time to obtain solution to a problem, e.g. a design problem.

In the recent decades, artificial intelligence techniques have emerged as a robust tool to replace time consuming procedures in many scientific or engineering applications.

The artificial neural networks are organized by processing units, which are called artificial neurons. An artificial neuron is a simple model of a biological neuron. Artificial neural networks are composed from a set of artificial neurons, which are arranged on a set of layers. There are nonlinear activation functions between various layers of a network. One of the most important characteristics of neural networks is learning. Learning may be supervised or unsupervised depending on the topology of networks. Therefore, topology, training or learning method and kind of activation functions of a network are the basic characteristics associated with the corresponding neural network.

Artificial neural networks have two operation modes, training mode and normal mode. In training mode, adjustable parameters of networks are modified. These adjustable parameters represent the strength of connection of a neural network. In normal mode, the trained networks are applied for the simulation or prediction of outputs. The use of neural networks to predict finite element analysis outputs has been studied previously in the context of optimal design of structural systems and also in some other areas of structural engineering applications, such as structural damage assessment, structural reliability analysis, finite element mesh generation or fracture mechanics[Hajela and Berke(1991), Berke et al(1993), Shieh(1994), Adeli and Hyo(1995a), Arslan and Hajela(1997) and Papadrakakis et al(1998)]. Neural networks have been recently applied to the solution of the equilibrium equations resulting from the application of the finite element method in connection to reanalysis type of problems, where a large number of finite element analyses are required. Reanalysis type of problems is encountered, among others, in the reliability analysis of structural systems using Monte Carlo simulation and in

structural optimization using evolutionary algorithms such as evolution strategies (ES) and genetic algorithms (GA). In these problems, neural networks have been proven to work very satisfactorily[Adeli and Hyo(1995b), Stephens and VanLuchene(1994), Papadrakakis et al(1996), Topping and Bahreininejad(1997) and Khan et al (1993)].

The principal advantage of a properly trained neural network is that it requires a trivial computational time to produce an approximate solution to a very complex problem with sufficient accuracy. Such approximations, if acceptable, appear to be valuable in situations where the actual response computations are intensive in terms of computing time and a quick estimation is required. For each problem a neural network is trained utilizing information generated from a number of properly selected analyses. The data from these analyses are processed in order to obtain the necessary input and output pairs, which are subsequently used to produce a trained neural network. Computationally, the training of a neural network is equivalent to an unconstrained minimization problem where the objective is to minimize the prediction error.

As can be seen from the above description, a neural network has to be properly trained and tested. For the development of neural network based tool for optimal design of double layer grid structures, proper training and testing using data of optimization are needed. For this purpose, the optimization procedures using SPSA proposed in this study can be used to generate training and testing data. As there are many models of neural network, it is essential that study be carried out to choose the model which yields prediction with acceptable errors. For this purpose, two

existing neural network models have been chosen to predict the optimal design and maximum deflection of double layer grid space structures. For comparison purpose, the commonly used backpropagation(BP) neural network has also been tested. Comparison with the two chosen artificial neural network have also been carried out. The developed neural network based tool is used to predict optimal design and the corresponding maximum deflection of double layer grid structures.

1.5 Problem Statement

To solve an optimal design problem of space structures, it is necessary to minimize the weight of the structure under a number of constraints on stresses and displacements. The design variables of such optimization problem are usually cross-sectional areas of the structural elements in the corresponding structure. Due to practical requirement of structural design, apart from cross-sectional areas, span (L) and height (h), of the double layer grids are also varied. Consideration of L and h to be varying means that the optimal cross-sectional areas should be found for each set of specified L and h . This means that as many optimization problems as the number of sets of (L, h) should be solved which necessitates a huge number of structural analyses to be carried out. The computational time of such problem is very high. Therefore it is important to substantially reduce the mentioned computational time for practical design purpose. This study is devoted to deal with this important problem by developing a tool for optimization of double layer grids where artificial neural network techniques is employed. Tools for prediction of analysis during optimization and prediction of design have been developed where the power of ANN

is fully utilized for time saving purpose. Nevertheless, a tool for the prediction of optimal design making use of the power of ANN has not been developed. Availability of such tool involving neural network technique as design aid to directly predict the optimal design (Figure 1.7) is expected to result in significant saving in time in the process of designing a cost-effective double layer grid structure.

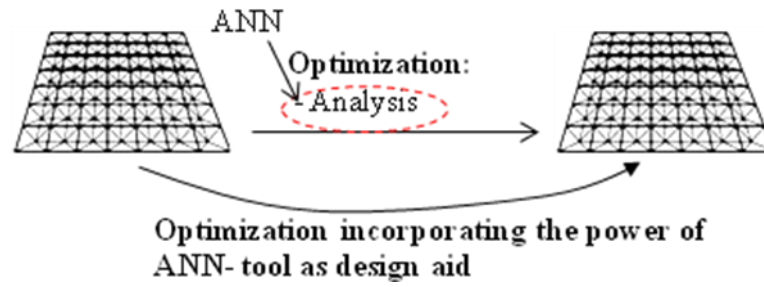


Figure 1.7: Prediction of optimal design of double layer grid structures

However, the neural network based computational tool mentioned above must be properly trained with a proper set of quality data obtained from results of optimization. As the typical number of elements involved in double layer grids is substantial, optimization of such kind of problem is a time consuming work. The factor of large size or degrees of freedom of problem in combination with the necessity of generating sufficient set of data for training and testing of neural network call for proper selection of optimization methods which are computationally efficient: methods with faster rate of convergence and ability to attain global solutions. A method of optimization with gradient-based algorithm whereby saving in time in the calculation of gradient by means of proper formulated approximation can be achieved is desired especially for the problem treated in this study. For the formulation of approximation for the calculation of gradient in optimization method,

stochastic approximation is an attractive option. The advantage of stochastic approximation is elaborated in Chapter 3.

1.6 Objectives

In view of the time consuming nature of the determination of optima design of double layer grids due to their large number of members and the necessity of a computational tool which can lead to significant saving in time, the current study has been carried out with the following objectives:

- i. To propose an analysis procedure for size optimization of double layer grid structures by combining finite element method, simultaneous perturbation method and artificial neural network
- ii. To compare the computational advantages of selected neural network types in the prediction of optimal design and maximum deflection of square-on-square double layer grids

1.7 Scope of Work

Two main steps are involved in this research study in order to develop a computational tool for predicting the optimal design of square-on-square double layer grids: i. data generation and ii. neural network training as shown in Figure 1.8. Within the data generation step, constrained optimization is carried out to generate data of cross-sectional areas and the corresponding maximum deflection for optimal

design. These generated data are then used in the neural network training step. Finite element method is adopted as the structural analysis tool during optimization.

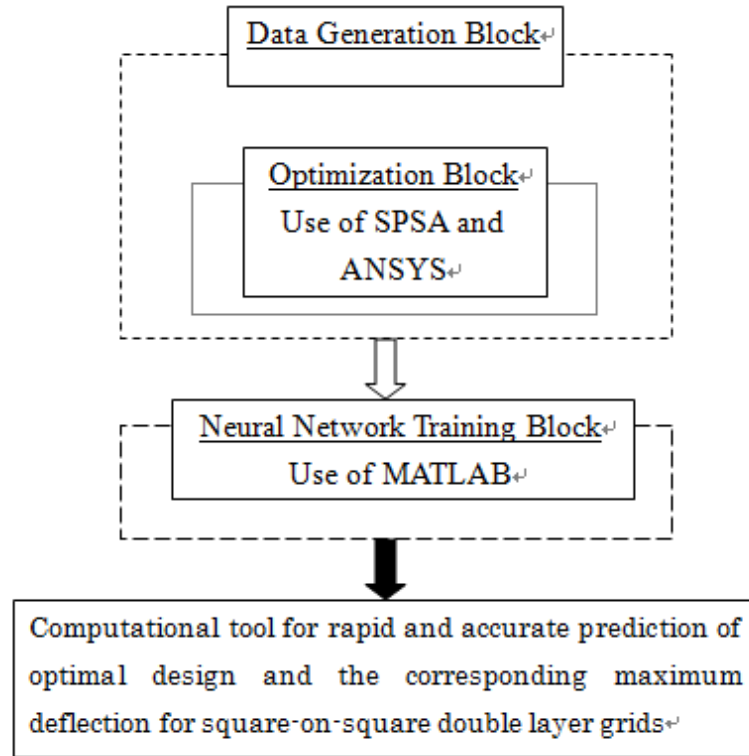


Figure 1.8 Major steps involved in the research study

1.8 Layout of Thesis

This thesis is divided into six chapters. The introduction, including an overview of space structures, optimal design of space structures, neural network, problem statement and objectives are presented in Chapter 1. Chapter 2 is devoted to literature review covering structural optimization and use of neural network in structural engineering. Basic formulation and equations used in the type of optimization carried out in this study, three artificial neural networks models, SPSA optimization

algorithm are presented in Chapter 3. The main steps of the proposed methodology in this study are presented in Chapter 4. Chapter 5 presents the numerical results and discussion. Finally, conclusions and suggestions for future work are described in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

Analysis procedure for optimization of double layer grid structure in this study makes use of finite element method(FEM), optimal solution seeking algorithm and artificial neural networks(ANN). Finite element method(FEM) has matured as a field with application to many diverse engineering problems since its modern development in 1940s. Its crucial role in the analysis procedure proposed in this study is the evaluation of structural response necessary in the process of finding an optimal solution. Review of related research studies presented in this chapter focuses only on development in the research studies related to structural optimization and use of ANN in the solution of civil and structural engineering problems. Related past studies on space structures are particularly emphasized.

2.1 Research on Structural Optimization

Structural optimization is aimed at finding design variables that will minimize or maximize certain objective function under different conditions of constraint. The focus of research studies about structural optimization is primarily aimed at : i. finding more efficient algorithm to speed up the optimization process, ii. finding better approach to located as far as possible global minimum or maximum points, iii. application to problems that involve more than one objective functions and iv. application to problems that involve more complicated conditions to be satisfied. Past research studies in the last decades on structural optimization with special attention to studies involving space structures are described below.

In order to deal with discrete design variable problem under constraint related to dynamic characteristics of structure, Tong and Liu(2001) has proposed a two-step optimization procedures to minimum weight problem of truss structures. Dynamic characteristic of the constrained optimization problem due to the constraints on natural frequencies and frequency response has been treated by converting the problem into a zero-one programming problem. Feasibility of the zero-one programming approach has been demonstrated by solving discrete optimum truss design problem. Optimization involving discrete design variables was also considered by Erbaturo et al(2000). In order to handle the problem due to discrete nature of design variable, genetic algorithm(GA) has been adopted as the optimizer. Application of GA to find suitable steel profiles in the optimal design of planar and space structures has been carried out. Comparison with other methods for handling discrete design variable problems were also made. Erbaturo et al(2000) concluded although GA was found to be more efficient than other methods, it was observed that GA found the region of search space containing the global optimum rather than the true optimum itself. A multilevel optimization was proposed to overcome the above mentioned problem. GA which is inspired by evolutionary process in nature has been much studied and applied. Wang and Tai(2004) applied GA to problem involving structural topology optimization problem. For the representation of structural topology, graph theory was made use of. Performance of the so-called graph representation GA has been compared with other methods. It was found that, graph representation GA was better in global search than GA where power-law approach was adopted. However, the computational time required was higher. Adaptive approach in GA coupled with proper member grouping strategy has been