TOPOLOGY OPTIMIZATION OF TRUSS STRUCTURES

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Civil Engineering

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April 2019

DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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ABSTRACT

Topology optimization is structural optimization that deals with additional and removal of structural elements to determine the best structural configuration or layout. Structural optimization is challenging as it includes generating all the different topologies to search for the finest topology. The generation of finest topology is essential to construction industry as it give the best structural design with minimum quantity of materials and construction cost and at the same time maximize its performance. Structural optimization is challenging due to large number of steel profiles available in the market and discrete in value of the cross-sectional area of the steel sections. Besides, an optimization approach that able to obtain optimal results at high accuracy but required high computational time will lead the optimization become costly. For economic purpose, this high accuracy optimization approach is less likely to be used in construction industry. Thus, an efficient optimization approach is required to obtain an optimal truss topology that provide a good balance between safety and economy. The aim of this study is to develop an approach to optimize the truss structure in terms of its weight and strength. In this study, topology optimization for eleven, sixteen and twenty-one element ground structure trusses subjected to static constraints (i.e. stress and displacement) are optimized by using Harmony Search (HS). The results obtained from the proposed optimization approach are compared with the SCIA Engineer software. The overall accuracy of the results obtained from HS based on eleven, sixteen and twenty-one element ground structure trusses are 96.25% and 99.82% for displacement of nodes and element stresses respectively. Besides, the redundant truss elements and joints can be identified at the end of the structural optimization. HS is also able to determine the best optimal connectivity between the structural members based on the amount and location of the load applied to generate an optimal truss structure with minimum weight. Thus, HS is one of the optimization approach to solve structural optimization problems that are mostly discrete and high complexity.

TABLE OF CONTENTS

DECLARATION			**ii**
APPROVAL FOR SUBMISSION			**iii**
ABSTRACT			**v**
TABLE OF CONTENTS			**vi**
LIST OF TABLES			**ix**
LIST OF FIGURES			**xii**
LIST OF SYMBOLS / ABBREVIATIONS			**xv**
LIST OF APPENDICES			**xvi**
CHAPTER			
1	**INTRODUCTION**		**1**
	1.1	Research Background	1
	1.2	Problem Statement	5
	1.3	Aim and Objectives	6
	1.4	Significance of the Study	6
	1.5	Scope and Limitation of the Study	7
	1.6	Timeline of Work	7
	1.7	Outline of the Report	9
2	**LITERATURE REVIEW**		**10**
	2.1	Introduction	10
	2.2	Meta-Heuristic Algorithm	12
		2.2.1 Genetic Algorithm (GA)	12
		2.2.2 Simulated Annealing (SA)	15
		2.2.3 Swarm Intelligence	18
		2.2.4 Harmony Search algorithm (HS)	22
	2.3	Summary	28

3	**METHODOLOGY**		**32**
	3.1	Introduction	32
	3.2	Ground Structure Method	32
	3.3	Finite Element Method	34
	3.4	Optimization Procedure of Truss Topology	35
		3.4.1 Step One: Define the Ground Structure of the Truss	37
		3.4.2 Step Two: Define Structural Optimization Problem and Harmony Search's (HS) Parameters	37
		3.4.3 Step Three: Randomly Generate Set of Truss Elements and Check the Validity of the Truss Structure	38
		3.4.4 Step Four: Truss Analysis	39
		3.4.5 Step Five: Constraints Checking	39
		3.4.6 Step Six: Improvisation of Harmony Memory	40
		3.4.7 Step Seven: Revision of Harmony Memory	41
		3.4.8 Step Eight: Check the Termination Criteria	41
		3.4.9 Step Nine: Output of Optimal Result	41
	3.5	Model Development	41
	3.6	Summary	43
4	**RESULTS AND DISCUSSION**		**44**
	4.1	Introduction	44
	4.2	Validation	44
		4.2.1 Validation of the Eleven Elements Ground Structure Truss	44
		4.2.2 Validation of the Sixteen Elements Ground Structure Truss	48
		4.2.3 Validation of the Twenty-One Elements Ground Structure Truss	56
	4.3	Discrepancy of the Results	68
	4.4	Simulation Time	69
	4.5	Summary	70

5	**CONCLUSION AND RECOMMENDATION**	**73**
5.1	General Conclusion of Research Work	73
5.2	Recommendations for Future Work	74
REFERENCES		**75**
APPENDICES		**80**

LIST OF TABLES

Table 2.1:	Analogous of Improvisation of Music with HS Optimization Method	24
Table 2.2:	Main Features of the Optimization Algorithms	30
Table 4.1:	The Best Cross-Sectional Area of Optimal Truss Structure for Eleven Elements Truss	46
Table 4.2:	Nodal Displacements of Optimal Truss Structure for Eleven Elements Truss	46
Table 4.3:	Element Stresses of Optimal Truss Structure for Eleven Elements Truss	47
Table 4.4:	The Best Cross-Sectional Areas of Optimal Truss Structure for Sixteen Elements Truss Subjected to First Load Case	50
Table 4.5:	Nodal Displacements of Optimal Truss Structure for Sixteen Elements Truss Subjected to First Load Case	50
Table 4.6:	Element Stresses of Optimal Truss Structure for Sixteen Elements Truss Subjected to First Load Case	51
Table 4.7:	The Best Cross-Sectional Areas of Optimal Truss Structure for Sixteen Elements Truss Subjected to Second Load Case	54
Table 4.8:	Nodal Displacements of Optimal Truss Structure for Sixteen Elements Truss Subjected to Second Load Case	54

Table 4.9: Element Stresses of Optimal Truss Structure for Sixteen Elements Truss Subjected to Second Load Case 55

Table 4.10: The Best Cross-Sectional Areas of Optimal Truss Structure for Twenty-One Elements Truss Subjected to First Load Case 58

Table 4.11: Nodal Displacements of Optimal Truss Structure for Twenty-One Elements Truss Subjected to First Load Case 59

Table 4.12: Element Stresses of Optimal Truss Structure for Twenty-One Elements Truss Subjected to First Load Case 59

Table 4.13: The Best Cross-Sectional Areas of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Second Load Case 62

Table 4.14: Nodal Displacements of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Second Load Case 63

Table 4.15: Element Stresses of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Second Load Case 63

Table 4.16: The Best Cross-Sectional Areas of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Third Load Case 66

Table 4.17: Nodal Displacements of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Third Load Case 67

Table 4.18: Element Stresses of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Third Load Case 67

Table 4.19: Simulation Time for Optimization of Eleven Elements Ground Structure Truss 69

Table 4.20: Simulation Time for Optimization of Sixteen Elements Ground Structure Truss 69

Table 4.21: Simulation Time for Optimization of Twenty-One Elements Ground Structure Truss 69

Table 4.22: The Optimal Results Obtained for Eleven Elements, Sixteen Elements and Twenty-One Elements Ground Structure Truss 72

LIST OF FIGURES

Figure 1.1:	Akutagawa River Side in Takatsuki, Japan, 2004 (Januszkiewicz and Banachowicz, 2017)	2
Figure 1.2:	Crematorium in Kakamigahara Gifu, Japan (Pugnale and Sassone, 2015)	2
Figure 1.3:	Type of Structural Optimization (Lee, 2012)	3
Figure 1.4:	Timeline of the Study	8
Figure 2.1:	GA Stages	14
Figure 2.2:	Illustration of Annealing Process in Material Science	16
Figure 2.3:	Flowchart of SA Algorithm	17
Figure 2.4:	Flowchart of PSO Algorithm	20
Figure 2.5:	Flowchart of ACO Algorithm	22
Figure 2.6:	Analogy Between Engineering Optimization and Music Improvisation	23
Figure 2.7:	Flowchart of HS Algorithm	25
Figure 2.8:	The Value of HS Algorithm Parameters Used for Structural Optimization (Lee, et al., 2011)	26
Figure 2.9:	The Optimal Results of Twenty Five Bar Space Truss with Other Optimization Methods (Lee, et al., 2011)	27
Figure 3.1:	Graph Theory (Kaveh and Kalatjari, 2003)	33
Figure 3.2:	Two Dimensional Truss Element	34
Figure 3.3:	Truss Topology Optimization Flowchart Using HS	36
Figure 3.4:	Graph of Weight per Unit Length against Cross-Sectional Area	38
Figure 3.5:	User's Input to Generate a Six Members Truss Structure	42

Figure 3.6: Six Members Ground Structure Truss Before Optimization 42

Figure 3.7: Optimal Truss Structure of Six Members Ground Structure After Optimization 43

Figure 4.1: Ground Structure of Eleven Elements Truss 45

Figure 4.2: Optimal Truss Structure of Eleven Elements Truss 45

Figure 4.3: Optimal Truss Structure of Eleven Elements Truss with Naming of Nodes and Elements 46

Figure 4.4: Ground Structure of Sixteen Elements Truss Subjected to First Load Case 48

Figure 4.5: Optimal Truss Structure of Sixteen Elements Truss Subjected to First Load Case 49

Figure 4.6: Optimal Truss Structure of Sixteen Elements Truss Subjected to First Load Case with Naming of Nodes and Elements 49

Figure 4.7: Ground Structure of Sixteen Elements Truss Subjected to Second Load Case 52

Figure 4.8: Optimal Truss Structure of Sixteen Elements Truss Subjected to Second Load Case 53

Figure 4.9: Optimal Truss Structure of Sixteen Elements Truss Subjected to Second Load Case with Naming of Nodes and Elements 53

Figure 4.10: Ground Structure of Twenty-One Elements Truss Subjected to First Load Case 57

Figure 4.11: Optimal Truss Structure of Twenty-One Elements Truss Subjected to First Load Case 57

Figure 4.12: Optimal Truss Structure of Twenty-One Elements Truss Subjected to First Load Case with Naming of Nodes and Elements 58

Figure 4.13: Ground Structure of Twenty-One Elements Truss Subjected to Second Load Case 61

Figure 4.14: Optimal Truss Structure of Twenty-One Elements Truss Subjected to Second Load Case 61

Figure 4.15:	Optimal Truss Structure of Twenty-One Elements Truss Subjected to Second Load Case with Naming of Nodes and Elements	62
Figure 4.16:	Ground Structure of Twenty-One Elements Truss Subjected to Third Load Case	65
Figure 4.17:	Optimal Truss Structure of Twenty-One Elements Truss Subjected to Third Load Case	65
Figure 4.18:	Optimal Truss Structure of Twenty-One Elements Truss Subjected to Third Load Case with Naming of Nodes and Elements	66
Figure 4.19:	Bar Chart of Average Time Taken for Respective Ground Structure to Find a Best Optimum Solution	70

LIST OF SYMBOLS / ABBREVIATIONS

$[F]$	force vector
$[K]$	stiffness matrix
$[\delta]$	displacement vector
A	cross-sectional area of steel sections, mm^2
L	element length, mm
E	Young's modulus of steel, MPa
σ	elemental stress, MPa
GA	genetic algorithm
SA	simulated annealing
PSO	particle swarm optimization
ACO	ant colony optimization
HS	harmony search
HMS	harmony memory size
HMCR	harmony memory considering rate
PAR	pitch adjustment rate
HM	harmony memory

LIST OF APPENDICES

APPENDIX A: MELEWAR STEEL TUBE SDN. BHD's Steel Sections Catalogue	80
APPENDIX B: SCIA Engineer Structural Analysis Reports	81

CHAPTER 1

INTRODUCTION

1.1 Research Background

Optimization is the process of finding an alternative that can maximize the desired factors while minimizing the less desired ones to give the best performance under certain constraints (Belegundu and Chandrupatla, 2011). In real world situation, the stiff competition in market place and consumer demands often required an optimum solution instead of feasible solutions for a given problem (Parkinson, et al., 2013). Therefore, many industries often look for the best approach through optimization process to meet their objectives and maximize profits (Ezema and Amakom, 2012). For example, mass-production corporations adopted optimization process to utilize the corporation's resources in mass-produced parts which result in significant savings for the corporations. Besides, the optimization process also widely applied in construction industry to determine the best structural design with minimum quantity of materials and construction cost and in the same time give the best performance in terms of stability, stiffness and strength (Sariyildiz, et al., 2015).

There are several examples of construction industry adopting optimization in their structural design. First of all, the optimization process was applied in the design of the world's second tallest building located in Hong Kong "Kowloon Mega Tower" at 474 m to minimize the construction material cost while maximize the floor space by considering the area of vertical walls and columns (Baldock, 2007). In addition, the design of the "Akutagwa River Side Building" in Japan as shown in Figure 1.1 was optimized to obtain the best shape of concrete structures (Januszkiewicz and Banachowicz, 2017). Furthermore, structural engineers in Japan also applied optimization process in the structural design of Crematorium as shown in Figure 1.2 located in Kakamigahara Gifu to determine an efficient structural shape (Januszkiewicz, 2013).

Figure 1.1: Akutagawa River Side in Takatsuki, Japan, 2004 (Januszkiewicz and Banachowicz, 2017)

Figure 1.2: Crematorium in Kakamigahara Gifu, Japan (Pugnale and Sassone, 2015)

Structural optimization is not only applied on optimizing the building structures, it is also applied in optimizing truss structure as well (Couceiro, et al., 2016). Truss is a structure whereby several members are connected at joint which is referred as node and the members are subjected to either tension or compression under loading conditions (Tejani, et al., 2018). There are three categories of optimization in truss structures which are sizing optimization, shape optimization and topology optimization as shown in Figure 1.3. Size optimization is the process of finding the best cross-sectional areas of the structural members (Tejani, et al., 2018). Shape optimization is the process of determining the design of truss structures by adjusting the nodal positions (Kaveh and Talatahari, 2009). Topology optimization is the most general structural optimization that used to find an optimal connectivity between the structural member within a specified design domain with no initial assumptions about the geometry and shape of the structure itself. Therefore, it provide design freedom which make it become a powerful design tool (Verbart, 2015). Through topology optimization, the inefficient truss members that constitutes low stressed in materials will be removed. This will significantly reduce the material used in the design to achieve minimum weight of truss structure (Degertekin, et al., 2017).

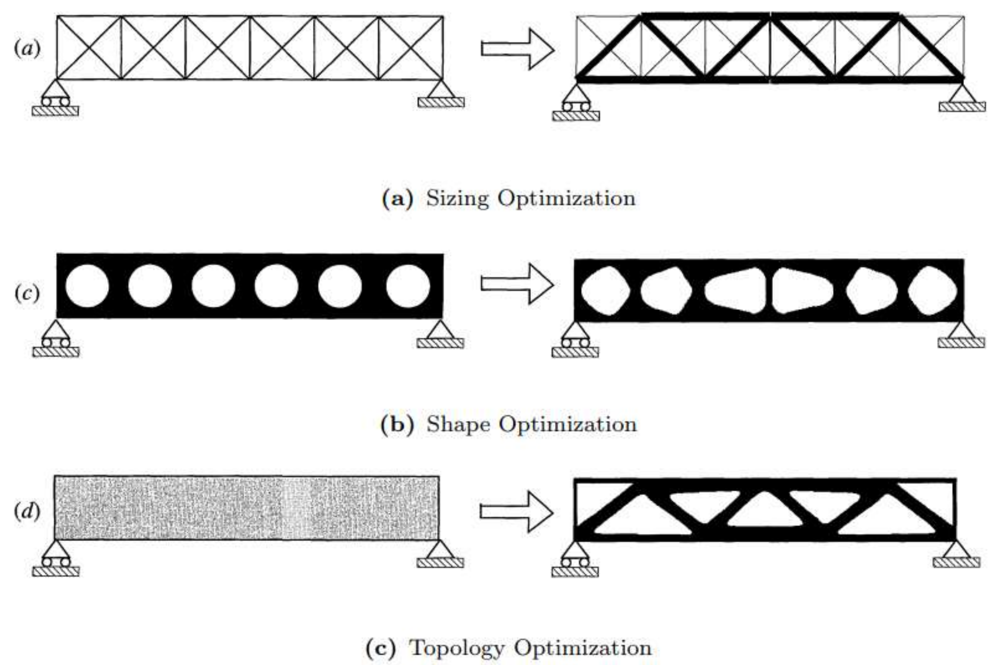

Figure 1.3: Type of Structural Optimization (Lee, 2012)

Optimization technique has been applied in construction industry thus, structural engineers required both theoretical knowledge and optimization techniques so that the optimization process can be applied practically to improve the structural design (Belegundu and Chandrupatla, 2011). Previously, civil engineers adopt a combination of judgement, past experiences and modelling decide on an optimal truss structure while performing the topology optimization for truss structure. However, these experience-based optimization process is ineffective if the optimization process is carried out with numerous variables to comply with constraints which need to be considered in the real-world applications (Parkinson, et al., 2013). Therefore, a computer-based optimization is preferred to perform the complicated design processes through optimization algorithm (Parkinson, et al., 2013).

Two categories involved in optimization algorithms are mathematical and nature-inspired (Lin, et al., 2012). The traditional mathematical approaches are not practically used in optimizing structures due to its high non-linearity and large discrete design variables (Yang, et al., 2016). Thus, some researchers utilized stochastic based nature-inspired algorithms which adopted probabilistic rule to deal with complicated design of structures (Lee and Geem, 2005).

The nature-inspired algorithms also known as meta-heuristic algorithms are commonly applied in complex engineering optimization problems due to its capability to obtain the optimized solution within reasonable amount of time (Gandomi et al., 2013). This is because meta-heuristic algorithms are derivative free and free from gradient computations, this allow it to overcome the drawbacks of traditional mathematical algorithms that require long computational time (Yang, 2014a).

In 2001, Geem, et al. (2001) has come out an optimization algorithm known as Harmony Search (HS) that inspired by nature of music to solve optimization problems. This music inspired algorithm make the engineering optimization works by using the harmony in music link to the optimization solution vector and the musician's improvisations link to the local and global search during performing the optimization process (Jaberipour and Khorram, 2010). The strong points of HS as an optimization tool are: (i) initial values is not required in performing optimization process; (ii) the searching of optimum result in HS is based on the harmony memory considering rate and pitch adjustment rate caused this algorithm does not perform any derivative mathematical calculation (Lee and Geem, 2005). Compared to other meta-heuristic algorithms, less mathematical calculation involve in HS cause this algorithm easier to implement in high complexity of engineering optimization problems (Yang, 2009).

In this study, HS is used to optimize the sizing and topology of the truss structure. The model will optimize the truss structure to find an optimal connectivity of the joints and its best cross-sectional area. Besides, the effectiveness of the optimization strategy implements in HS allows redundant truss and joints to be identified to achieve its minimum weight.

1.2 Problem Statement

In structure construction, the structural optimization is required to determine the best structure design that is neither yielded, buckled, nor deflected excessively in achieving its minimum weight (Parkinson, et al., 2013). Structural topology optimization was carried out by considering the material properties and cross-section of the structural members as decision variables to obtain an optimal structure within an acceptable time that give the best performance in lifetime with minimum overall life-cycle cost. However, structural optimization is difficult to perform due to large number of steel profiles available in the market and discrete cross-sectional area of the steel sections. Besides, an optimization approach that able to obtain results at high accuracy but required high computational time will lead the optimization become costly (MuÈcke, 1999).

The deformation or deflections limit of a structure specified in design requirements caused the structure to be designed with sufficient stiffness. The structure stiffness can be effectively increased by adding the supports or providing larger size of the structural members. If the stiffness of a structure is maximized, this will lead to a stiffer structure with better performance in terms of safety. However, this might not be applicable in practical design due to aesthetic and economic purpose (Ji, 2003). For example, applying stronger structural members will lead to the increase in construction cost. Besides, if the structural members are not stiff enough, it can be damaged after service in some period of time. Therefore, the structure must be optimized to provide a good balance between safety and economy so that the structure is structurally efficient as well as aesthetically pleasing.

The structural optimization process often involved large number of design variables. The steel section lists provided by the manufacturers have large number of steel profiles that lead structural optimization difficult to perform (Saka, et al., 2016). Although some of the combinations can be eliminated by engineers using their own prior experiences in design process, however, this elimination is just a small amount compared to all the combinations available provided by the steel section list. Thus, high computational time is required to determine the best combination of steel sections which make this structural optimization become expensive and not practical in optimizing the truss structures.

In addition, traditional mathematical optimization algorithms perform structural optimization by assuming all the decision variables are in continuous.

However, the sizing of structural members provided by the manufacturers are discrete in value (Li, et al., 2009). Therefore, the used of traditional mathematical optimization method in structural optimization became impractical in performing the structural optimization. The structural optimization process must be performed with discrete design variables so that the optimal structure obtained in the optimization process is practically available in the manufacturing industry.

Non-linear mathematical programming is usually robust and applicable in all types of optimization problems. However, this method requires more mathematical calculations involve in objective functions, constraints and the derivatives to obtain the optimum result with high accuracy (Saka, et al., 2016). The structural optimization problems are mostly complex and often characterized by high dimensionality search space with multiple objective function. This will lead to an increase in computational time when the number of design variables and objective function increase which lead this method become very costly and time consuming.

In summary, engineering optimization is required to determine the best decision variables in order to prevent the wastage of resources in term of cost, time and materials. HS is an efficient approach in structural optimization due to its derivative free and user friendly to allow the best optimal result can be obtained in short computational time with sufficient accuracy.

1.3 Aim and Objectives

The aim of this study is to optimize the truss structure in terms of its weight and strength. There are three objectives to present in this study as listed below:

i. To develop an approach for optimizing the topology of truss structures
ii. To obtain an optimal joints connectivity to produce a truss structure with minimum weight
iii. To determine redundant truss elements and joints

1.4 Significance of the Study

The significance of this research is to determine the best design of truss structure that satisfy all the specified design requirements such as the allowable deformation and maximum stress taken by the structural members. The optimized design of truss structure in terms of mass, stiffness, stress and deformation allow the enhancement of structural performance to achieve structural efficiency and high reliability.

1.5 Scope and Limitation of the Study

The scope of work in this study is to optimize the truss structures and determine the best truss topology and sizing that give minimum weight. The study is limited to simple truss structure up to twenty-one structural members. Besides, the structural analysis performed in this study is two dimensional instead of three dimensional to make the optimization problems easy to handle. There are some assumptions made in the analysis of truss which are (i) Truss members are connected only at their ends; (ii) All loadings are applied only at the joints; (iii) The weight of the connection in between the truss member may be neglected. From the first two assumptions made in the truss analysis, each truss member acts as an axial force member.

1.6 Timeline of Work

The activities conducted in this study is shown in Gantt chart as indicated in Figure 1.4.

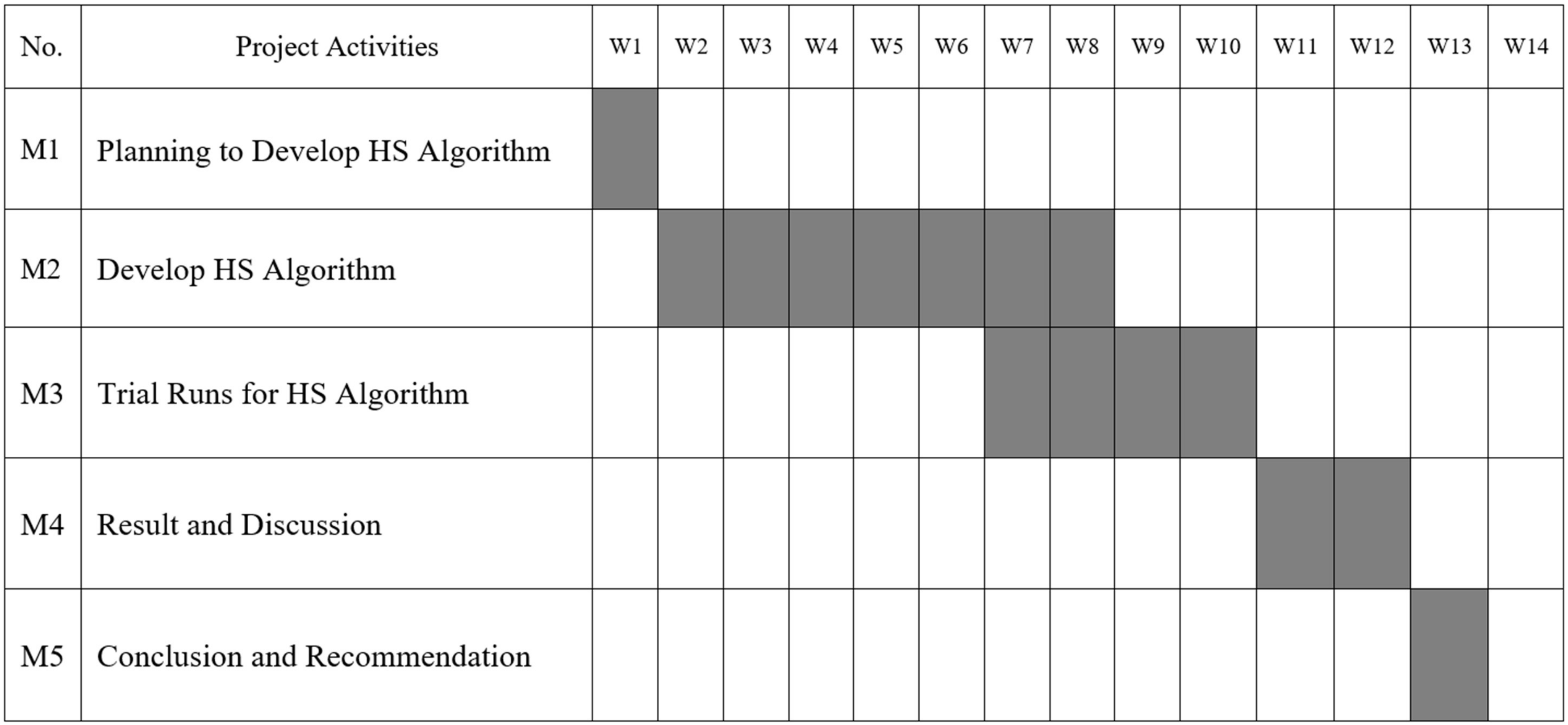

Figure 1.4: Timeline of the Study

1.7 Outline of the Report

This research report consists of five chapters which include introduction, literature review, methodology, results and discussions and conclusions and recommendations. In Chapter 1, a brief general introduction of the engineering optimization which provide the necessary information about the background of the study, problem statements, research's aim and objectives, significance of the study and scope and limitation of the study will be included in this chapter. Review of five most popular meta-heuristic algorithms in solving engineering optimization problems which include Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Harmony Search (HS) are discussed in Chapter 2. Explanation of the optimization procedure using HS to determine the best truss topology will be included in Chapter 3. Chapter 4 presents results on application of HS in solving eleven, sixteen and twenty-one element ground structure trusses and simulates validation of the proposed methodology using SCIA Engineer software. Discussion on the performance of the proposed methodology in solving structural optimization problems in terms of its validity, accuracy and simulation time are included in Chapter 4. Chapter 5 presents general conclusions of this study and recommendations for future work to improve the proposed methodology to solve high complexity of engineering applications.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Engineering optimization has grown rapidly over the last few decades to solve various problems in engineering field e.g. truss structures (Lin, et al., 2012). The optimization methods can be divided into deterministic and stochastic approaches (Lin, et al., 2012). The behaviour of an algorithm can be predicted completely from the input is known as deterministic algorithm. Deterministic algorithms is an algorithm that repeatedly follow a pre-set of rules and procedures and their outcome do not vary if the algorithm is repeated with the same inputs (Sun and Yang, 2006). Hill climbing is an example of deterministic algorithm where it operate the same path for the same starting point (Yang, 2010).

Most of the classical mathematical programming are mostly deterministic such as linear programming (LP) e.g. the simplex method, non-linear programming (NLP) e.g. geometric programming, quadratic programming (QP), and dynamic programming (DP) have been developed for finding a global or an approximately global optimum in optimization process (Lee and Geem, 2004). The mathematical programming methods in engineering optimization problems are mostly gradient based and derivative based (Lee and Geem, 2004).

The gradient based mathematical programming methods optimize a given continuous problem through the process of searching for a local optimum based on local gradient by assuming all the design variables varied continuously in the optimization process. The derivative based mathematical programming applied first and second order method to solve a set of non-linear equations for finding a local optimum in optimization problems.

Structural optimization is one of the discrete optimization problems. Initially, round-off techniques have been applied on discrete optimization problems to make it become continuous problems and solve it using mathematical programming. However, the solutions obtained is far from the optimum solutions (Li, et al., 2009). Besides, initial values and gradient computations are required to search for the optimum solutions. Therefore, the result obtained is affected by the selection of initial points. In addition, gradient search is difficult to perform when the optimization problems have multiple peaks on objective function and constraints. Thus, mathematical programming inefficient to use in this complex real-world structural optimization problems (Hasançebi, et al., 2009).

Unfortunately, complex engineering optimization problems are often characterized by high dimensionality search space, non-linear objective function and stringent constraints that causes deterministic methods difficult to derive an optimal solution within an reasonable time due to high complexity of the problems (Lin, et al., 2012). Besides, the engineering optimization problems are considered as deterministic if there is no uncertainty in the values of both design variables and objective functions. However, the parameters such as Young's Modulus can only measure up to a certain accuracy and most of the material properties of real materials are not uniform (Yang, 2010). This causes the design variables, objective functions and constraints are in the state of uncertainty. Therefore, structural optimization becomes a stochastic optimization problem that requires stochastic approaches to solve the problems.

Stochastic algorithms follow probabilistic rule in its search for the best approach such that the outcome of the algorithm would depend on specific realizations of the random components of the algorithms (Sun and Yang, 2006). In other words, the algorithms with same inputs in the same set of parameter values will give different outcome at each time the algorithm performed. Generally, there are two types of stochastic algorithms, heuristic and meta-heuristic. The difference between heuristic and meta-heuristic is small such that meta-heuristic is the higher level of heuristic methods that generally perform better than simple heuristics (Yang, 2014a). Heuristic is a method that discover an optimum solution by trial and error (Yang, 2014a).

Further development of heuristic algorithms is the meta-heuristic algorithms (Yang, 2014a). This algorithm is a stochastic algorithm with randomization and global exploration that utilize the ideas inspired from the nature. Meta-heuristic algorithms are applied in high complexity optimization problems with the aim of finding the quality solutions in short period of time, but the obtained solutions is not guarantee as the best solutions (Yang, 2014a). Meta-heuristic algorithms are derivative free and does not require any gradient computation (Yang, 2014a). Randomization is a good way to find a global optimum by avoiding the search process being trapped in local search correspond to local optimum.

Two major components that helps the system to obtain the optimum solutions are intensification and diversification. Intensification is known as exploitation where it helps the algorithm to utilizes the information obtained from current good solution found in a space to focus on the search of solutions in that local space. Diversification also known as exploration where it is a process in which the algorithm produces multiple solutions so that the searching space is explore on global scale. Exploitation will lead the current good solutions converge to optimality whereas the randomization in exploration will avoid the solutions being trapped in local optima. Therefore, a proper balance between this two components are required for a well design optimization algorithms to give the quality results (Kaveh and Zolghadr, 2014).

This nature-inspired algorithms can be used in various type of optimization problems including structural optimization using Harmony Search (HS) (Lee and Geem, 2004), mass minimisation of truss using meta-heuristic algorithms with dynamic constraints (Pholdee and Bureerat, 2014), steel truss optimization using Genetic Algorithm (GA) (Cazacu and Grama, 2014), optimization of truss structures with discrete variables using Particle Swarm Optimization (PSO) (Li, et al., 2009), design optimization of truss structures using Simulated Annealing (SA) algorithm (Lamberti, 2008) and optimization design of truss based on ant colony optimization (ACO) algorithm (Chen, et al., 2010).

2.2 Meta-Heuristic Algorithm

Most of the meta-heuristics are inspired by nature. The meta-heuristic can be grouped in different categories based on the source of inspiration in optimization. They are inspired by biology, evolution theory, music and physics. The most popular meta-heuristics are GA, SA, PSO, ACO and HS. The popular meta-heuristic algorithm will be described below:

2.2.1 Genetic Algorithm (GA)

GA is introduced by John Holland in 1960s (Holland, 1975). GA is an optimization technique that inspired by biological evolution. In GA, the encoding of an optimization function as character strings to represent them in chromosome, manipulation operations of strings by genetic operators which include crossover and mutation, and the selection process follows Darwinian survival of the fittest theory. The crossover and mutation in GA are stochastic in nature that causes the GA perform effectively in exploration of the search space to obtain global optimum solutions. Therefore, it is a popular global search algorithm that solve the optimization problems with high efficiency as it does not require any gradient computation, highly explorative and parallelism which are the advantages over the conventional mathematical method (Yang, 2014b).

Crossover, mutation and selection are the three keys operators of optimization process in GA. Crossover is the recombination of two parent chromosome by exchanging part of one chromosome with a corresponding part of another chromosome to produce off springs or new solutions. In mathematical way, crossover act as a local search operator which operate a mixing process with local search in a subspace to help the system converge. Mutation is a step taken to change part of a chromosome usually single or several parts of the chromosome to produce new genetic characteristics. Mutation act as a global search operator that allow the system to explore the search space globally. Hence, it generates diversity of new solutions and escape from local optimum. Crossover provides good mixing, but its diversity is limited to subspace while mutation provide better diversity, but it will cause the system to converge slower. Therefore, a balance must be provided between crossover and mutation to obtain the best quality solutions. In selection process, the highest quality chromosomes will be selected and remained in the population to ensure that the best gene is pass on to the next generations in the population and make the system converge (Yang, 2014b).

The first step needs to be taken to perform GA is to initialize the population by randomly generating the individuals which represent potential solutions of the optimization problems. The size of the populations is determined by the nature of the problem itself. For example, there are a lot of design variables present in complex optimization problems which lead the size of the population become larger. Next, a fitness function is used to evaluate the fitness of every single member within the population. Each member will be given a fitness value by employing the fitness function. Then, the fitness value will be used to sort the entire population in descending order. If the termination criterion is not met, crossover and mutation in selection stage will be carried out based on the best fitness value obtained from each individual to generate new solutions. The whole process is repeated until the stopping criteria is fulfilled. The stages performed by GA in optimization process are illustrated in Figure 2.1.

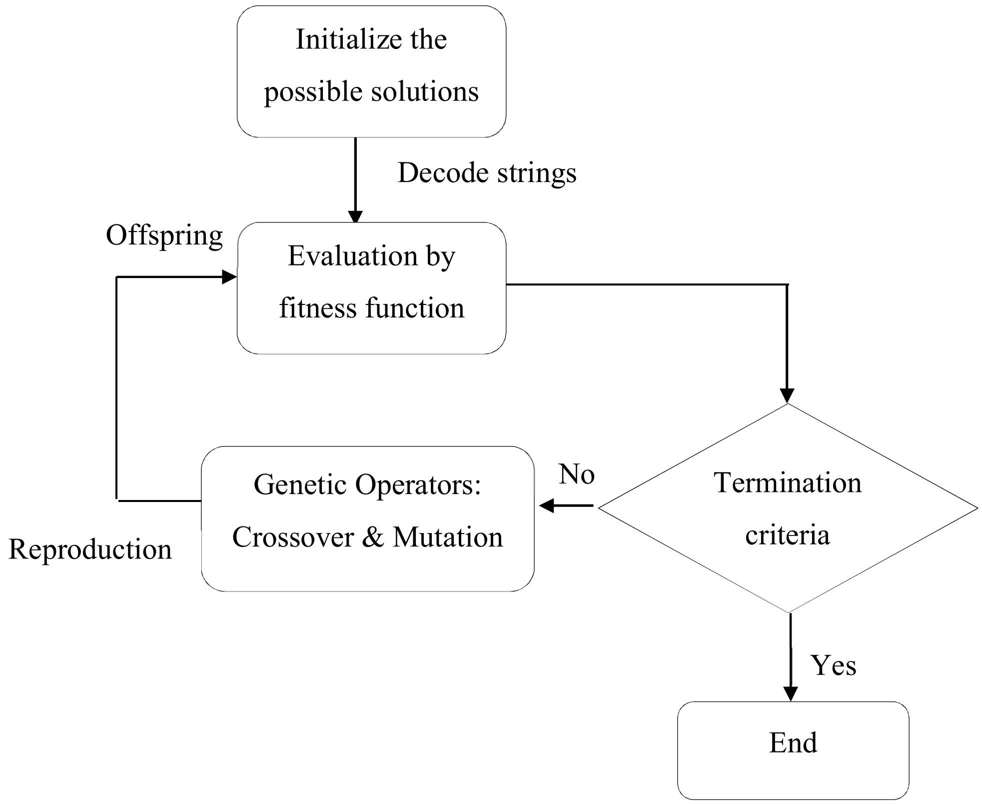

Figure 2.1: GA Stages

GA is applicable on solving tough structural optimization problems. For instance, GA was used for weight minimization of truss structures including space truss structure with twenty five and seventy two members and it also used to optimize plane truss structure with seventy two, two hundreds and nine hundreds and forty members (Dede, et al., 2011). Moreover, GA was used to optimize a truss structure that able to sustain under normal loading conditions and accidental loading condition to prevent the structure fail based on elastic-plastic analysis (Wang and Ohmori, 2013). Besides, GA and finite element analysis has been used to optimize steel truss structure by encoding all the trusses in chromosomes to simultaneously optimize the topology, shape and size of the truss structure that subjected stress and displacement constraints (Cazacu and Grama, 2014).

The implementation of GA is easier compared to alternative intelligent optimization algorithms (Zang, et al., 2010). Although GA is good in engineering optimization, it also has some disadvantages especially when the population size is small which will lead to local optimum or premature convergence. When the use of population size is small, a significantly fit individual appear earlier during the optimization process will reproduce the offspring that is fit enough to prevent the algorithm from seeing the whole population due to its small population. This will cause the system lack of exploration that eventually lead to a local optimum or premature convergence. However, when large population size is used, more objective functions are needed to determine the fitness of the individuals and thus increase the computing time (Yang, 2014c). Besides, GA only select two of the existing vectors to generate a new vector without considering each component in a vector. This will allow the system converge faster but a local optimum is likely to be obtain (Lee and Geem, 2005).

2.2.2 Simulated Annealing (SA)

SA is a trajectory-based search algorithm that keeps track of only one candidate solution. SA is inspired by the annealing process of metals (Kirkpatrick, et al., 1983). In the stages of metal annealing, the metal is initially heated up at high temperature to exert high energy on the atomic arrangement of metal until it melts. Breaking of bonding between the atoms due to high energy cause the molecules to move freely within the space. Then, the metal is left to cool slowly under a careful control of the temperature and cooling rate. Figure 2.2 shows an example on how the atomic arrangements in a material behave under cooling conditions.

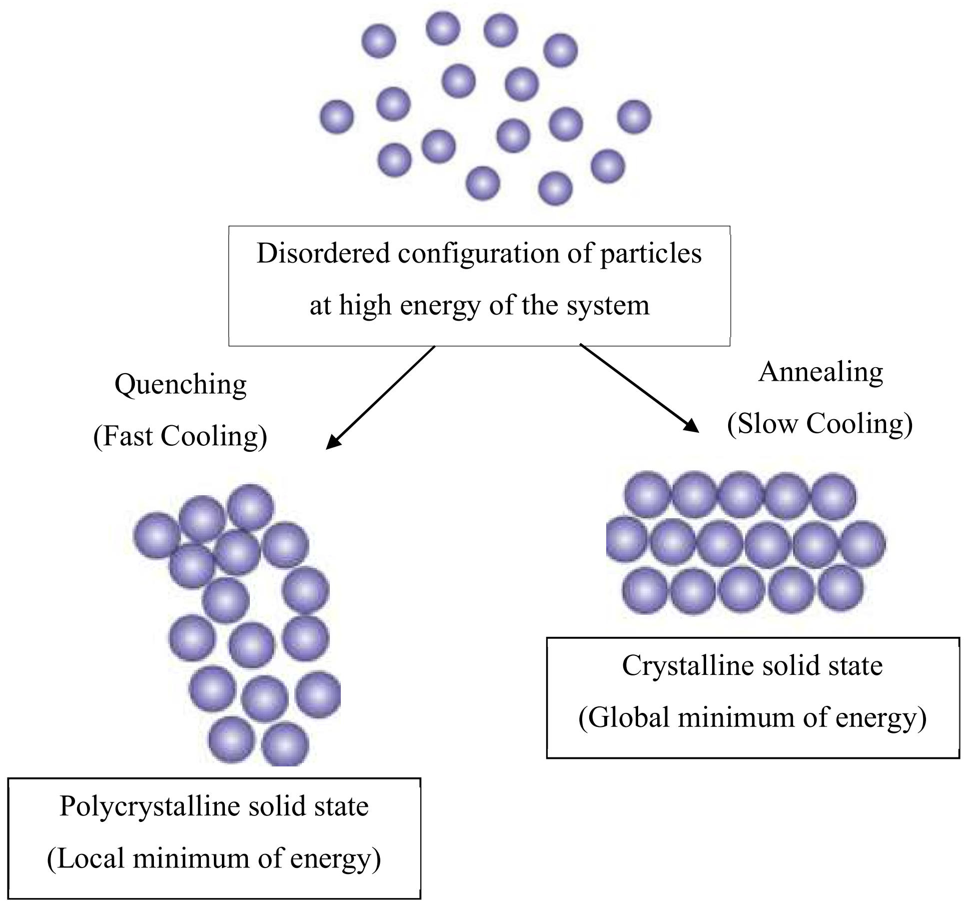

Figure 2.2: Illustration of Annealing Process in Material Science

In SA algorithm, the trial point is randomly created followed by evaluating it using objective function. The trial point will be rejected, and new trial point will be selected for evaluation when the trial point is found to be infeasible. On the other hand, when the trial point is feasible with better value of objective function, then the point is updated with the best objective value. However, when the trial point is found to be feasible but with poorer objective value, then the acceptation for this point is based on probabilistic criterion that determine whether the trial point may bring the system to achieve global minimum (Lamberti, 2008). From the analogy of the annealing process of a metal, the target value for the objective function is temperature. Firstly, a higher temperature is chosen as the trial point. Then the temperature is decrease according to the cooling rate as the trials continues. The probability to accept a new trial point will eventually decrease to zero as the target value diminished. Thus, the system is converged, and the global minimum is achieved. The flowchart of SA is shown in Figure 2.3.

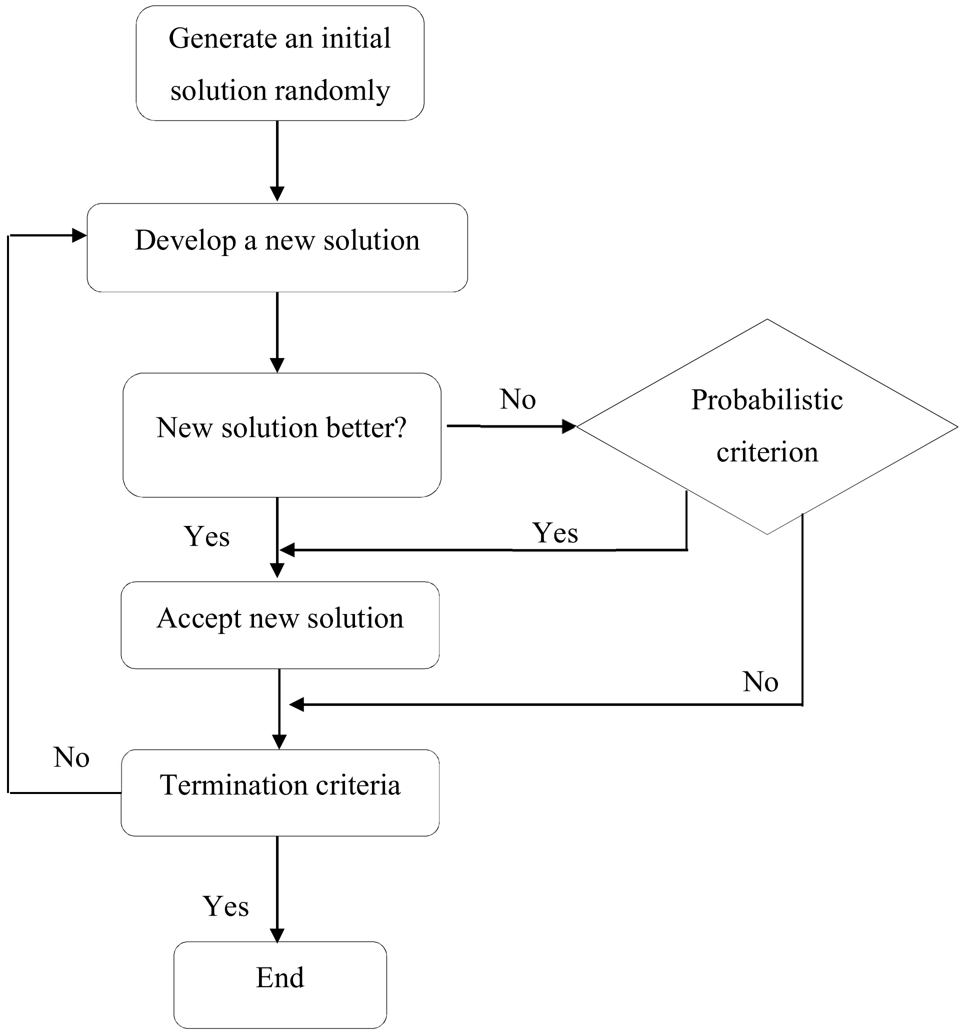

Figure 2.3: Flowchart of SA Algorithm

Simulated Annealing has been widely applied in complex engineering optimization problems due to its simplicity and ability to find the global optimum (Lamberti, 2008). For example, SA algorithm has been used for shape optimization of two dimensional structures to determine the best structure that fulfilled the design requirements (Sonmez, 2007). The optimization results obtained from SA are said to be comparable to those obtained from classical mathematical approaches (Bureerat and Limtragool, 2008). The structural optimization of lattice steel transmission towers based on SA algorithm was proposed to obtain a structure that use the minimum amount of materials to satisfied the design requirements (Couceiro, et al., 2016),

The main operator of SA is to generate a new solution through random search and this random search act as an explorative search mechanism to prevent the system being trapped in local optimal. However, a very high initial solution that has been chosen to perform the optimization process will cause the system to converge very slowly in practice due to large number of function evaluations was carried out to find the global optimum. This is because there is no crossover operator like GA in SA algorithm which can make the system converge faster (Yang, 2014b). Furthermore, SA is relatively weak in utilizing the information obtained from current good solution found in a space to concentrate on the search of solutions in that local space because the acceptance of solutions is carried out by probability criterion (Yang, 2014b). Therefore, the slow convergence behaviour of SA causes the computational time longer which is not practical in solving real-world optimization problems.

2.2.3 Swarm Intelligence

Swarm intelligence is a computational intelligence optimization system that inspired by the combination of natural and artificial systems. This system consists of many individuals in one population to coordinate their activities through exchanging information and sharing experiences among the individuals. The combination of movements and interactions among the individuals leads to an optimization of the activities in the population. Specifically, swarm intelligence simulate the social behaviour of animals like fishing schooling, birds flocking and colonies of ants (Cui and Gao, 2012). The most popular optimization algorithm that use the principles of swarm intelligence are PSO and ACO (Cui and Gao, 2012).

2.2.3.1 Particle Swarm Optimization (PSO)

PSO is a population based optimization method that introduced by Kennedy and Eberhart (1995). PSO algorithm simulates from the behaviour of animal societies that have no leader in their group. Usually, a flock of birds which have no leader in their group will seek for food source by random or follow one of the members of the group that has a nearest position with a food source. Assuming there is only one food source and considering at the other birds that are closer to the food source will move towards it with the aim of getting closer to the food source early compare to others. Each bird in a particular position trying to search for a bird which is in the best position and speed towards the best bird using a velocity. Therefore, it involves communication among the birds to find a global best position. This process would happen repeatedly until the bird found no other better position. Thus, the optimization problems based on PSO algorithm follows the behaviour of animal societies to find the optimal solutions (Rini, et al., 2011).

A swarm represent the population while a particle represents each member in the population (Luh and Lin, 2011). In PSO algorithm, every single particle of a swarm represent a possible solutions to the optimization problems (Rini, et al., 2011). Initially, each of the particles is randomly generated to form a swarm to travel around the search space with an initial position and velocity. The position and velocity are the two basic components of PSO algorithm which guide the system to converge towards the optimal solution (Agarwal and Vasan, 2016). Each of the particles would find their new position and velocity at the end of each iterations. The velocity of each particle at each iteration would influence the position of the particles. The new positions discovered by the particles are evaluated by the defined objective function to determine its fitness value while the velocities direct the particles follow the particle which is closer to optimum solution. In the search processes, PSO converges towards the optimum by improving the local position of each particle in iteration. This is done by updating the positions of the particles based on the best position taken by each of the particle and the global best position taken by the entire swarm (Mortazavi and Toğan, 2017). Thus, a global optimum solution will be achieved when the particles discovered no newer best position in the search space. The flowchart of PSO is illustrated in Figure 2.4.

Recently, PSO method is applied to optimize the truss structures with minimum weight under stress, deflection, and kinematic stability constraints. The results obtained using PSO algorithm require less computational time to produce a structure with minimum weight (Luh and Lin, 2011). Although PSO is good in engineering optimization, it also has some disadvantages. PSO has difficulties in providing a good balance between diversification and intensification due to the absent of crossover operator (Luh and Lin, 2011). A strongly selective process of global best solution in PSO algorithm may lead to premature convergence which is not the interest of optimization problems (Luh and Lin, 2011).

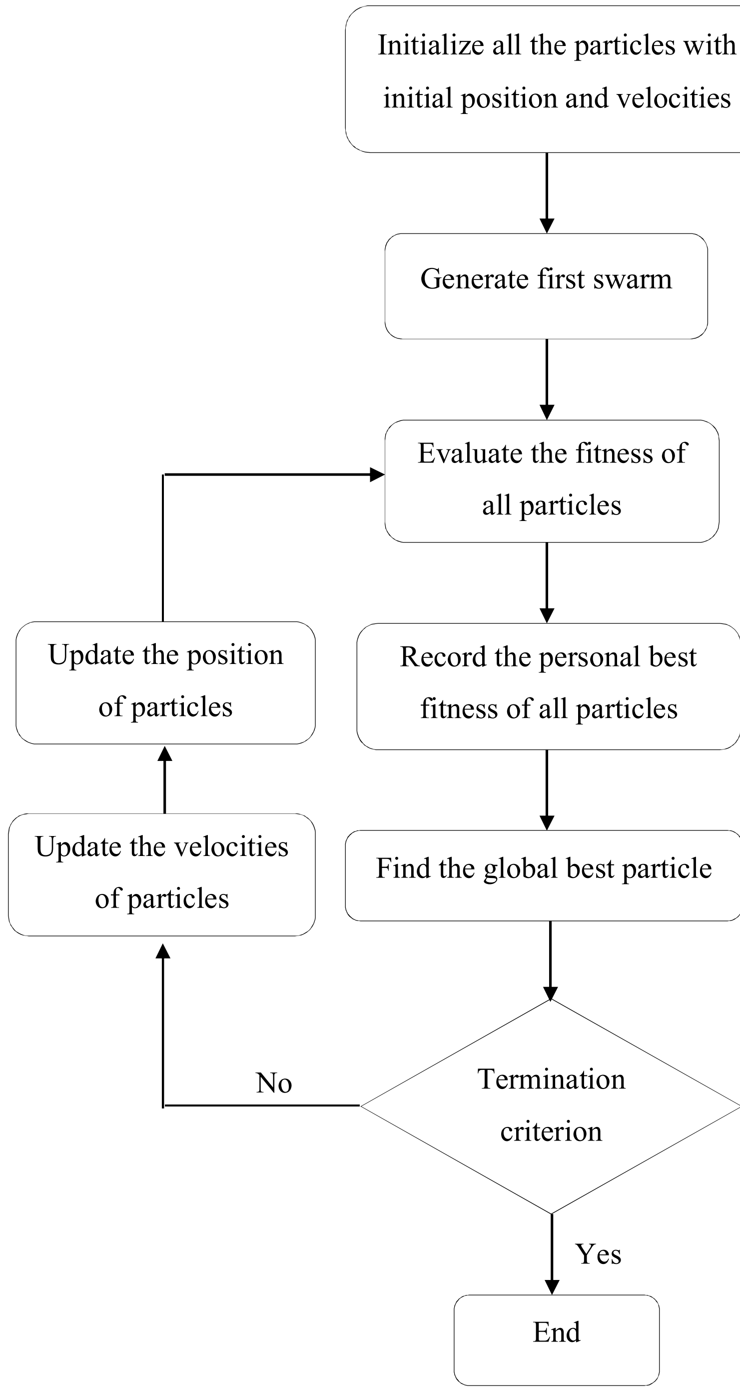

Figure 2.4: Flowchart of PSO Algorithm

2.2.3.2 Ant Colony Optimization (ACO)

ACO is an algorithm that simulates the foraging behaviour of real ants to solve optimization problems (Mavrovouniotis, et al., 2017). In real life situation, a colony of ants seeks for the shortest or closest food source from their nest by exploiting the chemical substance known as pheromone that previously deposited by other ants while walking to and from the food sources. As time goes by, a higher pheromone concentration path will consider as the shortest path to the food source and this path is more likely to be chosen by the ants to reach the food source.

ACO algorithm is an optimization method that adopted the probabilistic search by implementing a set of artificial ants where each of the ants represents a possible solution to a problem and exchange information to each other via the deposited pheromone to find the optimum path. There are two important parameters in ACO which is the probability function and evaporation rate. Probability function is a function that influenced the ants to choose the path with higher pheromone concentration. The probability of choosing the path by ants is proportional to the pheromone concentration (Yang, 2014d). Evaporation rate is a rate that evaporate the pheromone concentration with time. The advantages of using evaporation rate in ACO algorithm is able to prevent being trapped in local optimal (Yang, 2014d). This is because if there is no evaporation rate, the pheromone deposited by the first ant will be the preferred path due to the attraction of other ants by their pheromone (Yang, 2014d).

The optimization process of ACO is begin by initialize the ACO parameters. Then, the artificial ants are constructed to search for food sources randomly. By applying the probability function and evaporation rate, other ants will follow the path based on the pheromone intensity. The amount of pheromone concentration released is based on the objective values achieve in the objective function. Therefore, the concentration of pheromone is only update on the paths that lead to optimum solution which offer more pheromone concentration while diminishing the likelihood of the ants of choosing other paths. The updated pheromone matrix is used to generate the new path until the termination criteria is met. The flowchart of ACO algorithm is shown in Figure 2.5.

ACO is relatively good in diversification due to the design variables are randomly assign to each of the ants instead of searching a neighbourhood around the design variables. This allow the algorithm to have more opportunities to explore search space in globally manner (Alberdi and Khandelwal, 2015). ACO algorithm is successfully used in structural optimization as it is able to generate an optimal seismic design of frame structures (Kaveh, et al., 2010). It is also used is optimizing the structural topology problem where the problem are describe by mixed continuous discrete variables and discontinuous non-convex design space (Kaveh, et al., 2008).

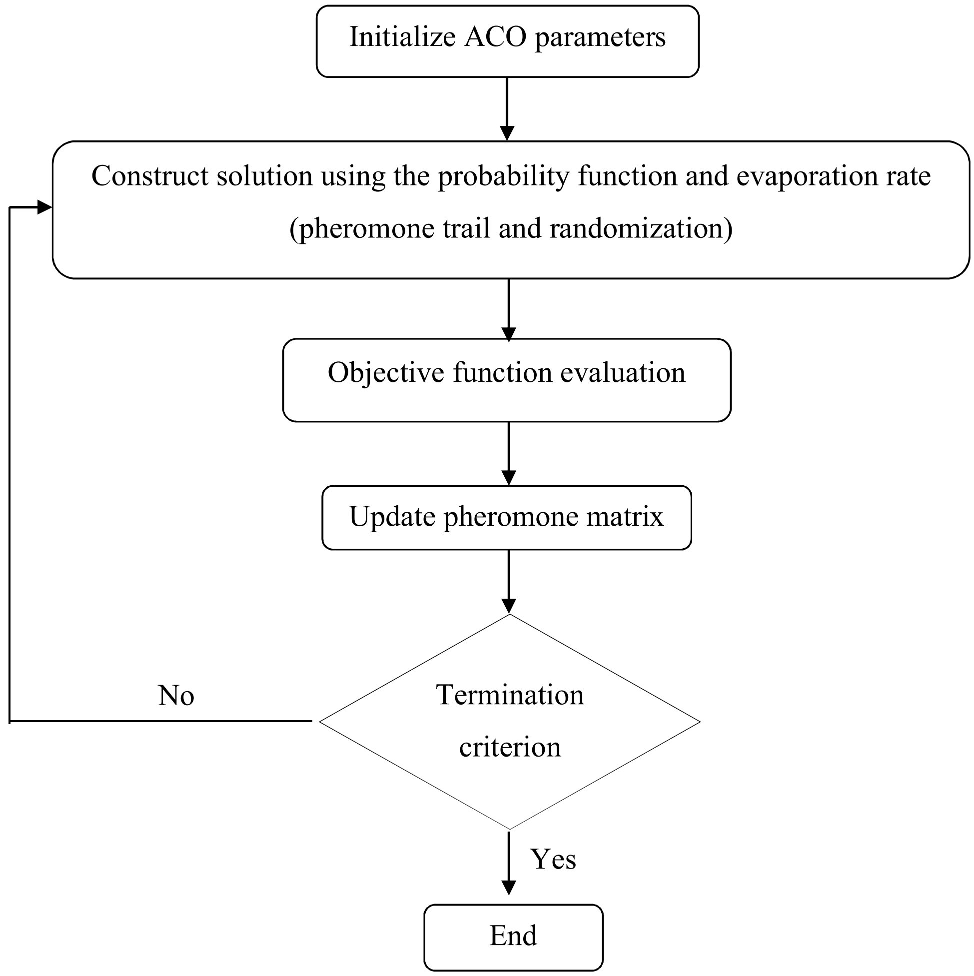

Figure 2.5: Flowchart of ACO Algorithm

Although ACO has proven that it is widely used in optimizing structural optimization problems, there are some weakness using ACO. The probability operator in ACO is the only operator that perform exploration and exploitation such that ACO is more focus on exploration at the early stage and exploitation at the later stage cause this algorithm is unable to balance between two in optimization process (Alberdi and Khandelwal, 2015). Besides, computational time of ACO in optimizing frame structure is very high which is not favourable in real life optimization process (Kaveh and Talatahari, 2010).

2.2.4 Harmony Search algorithm (HS)

HS optimization algorithm is introduced by Geem (2001). This algorithm is neither simulating the biological or physical process such as GA and SA. HS is a music-inspired algorithm with the aim to seek for the best harmony in music. The global optimal searching process in optimization are analogous to the improvisation of music from a musician to produce best state of music which is the global optimum solutions (Jaberipour and Khorram, 2010).

As illustrated in Figure 2.6, several musicians will play any possible range of pitch using their own musical instruments to form a harmony vector in the process of improvisation of music. The experience of making a good harmony from the possible range of pitches will be stored in each of the musician's memory at each play. The harmony state of the music will be enhanced in the next play based on the previous experiences of making a good harmony. This is similar to engineering optimization problems such that each of the decision variables is chosen initially within possible range to form a solution vector. The experience of making a good solution vector from the decision variables will be recorded in each of the variable's memory at one iteration and find the best solution vector from the possible range of design variables through several iterations (Lee and Geem, 2005).

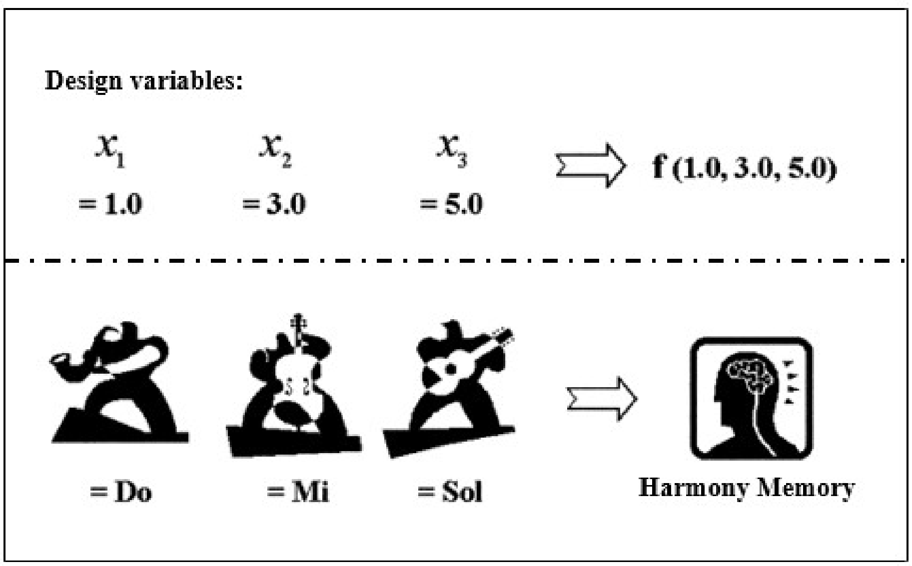

Figure 2.6: Analogy Between Engineering Optimization and Music Improvisation

There are three rules to link the creation of music to HS optimization method. All of the rules are presented in Table 2.1.

Table 2.1: Analogous of Improvisation of Music with HS Optimization Method

HS Components	Creation of Music's Rules	HS Optimization Method
Harmony Memory Consideration	Playing every sound from listener memory	Selecting every value from harmony search memory
Pitch Adjustment	Playing familiar sound to listener memory	Selecting value near to harmony search memory
Randomization	Playing random sound from possible sound range	Selecting random value from possible range of value

To use HS in optimization process, harmony search parameters such as the size of harmony memory (HMS), harmony memory considering rate (HMCR), pitch adjusting rate (PAR) and the maximum number of iterations must be defined initially. The harmony memory matrix is initialized by randomly select the design variables from the design pool. Next, the harmony memory is improved by three parameters in HS algorithm which is the HMCR, PAR and randomization to produce an improvised harmony memory. In the improvisation process, the new harmony vector that generated by improving the values for each decision variables will be evaluated by the objective function. The better harmony vector will be stored in the harmony matrix while the worst harmony vector will be withdrawn from the harmony matrix. Thus, the harmony matrix is updated by including the new harmony vector. The harmony matrix will keep updating until the termination criteria is satisfied. The flow chart of HS algorithm to illustrate the steps is shown in Figure 2.7.

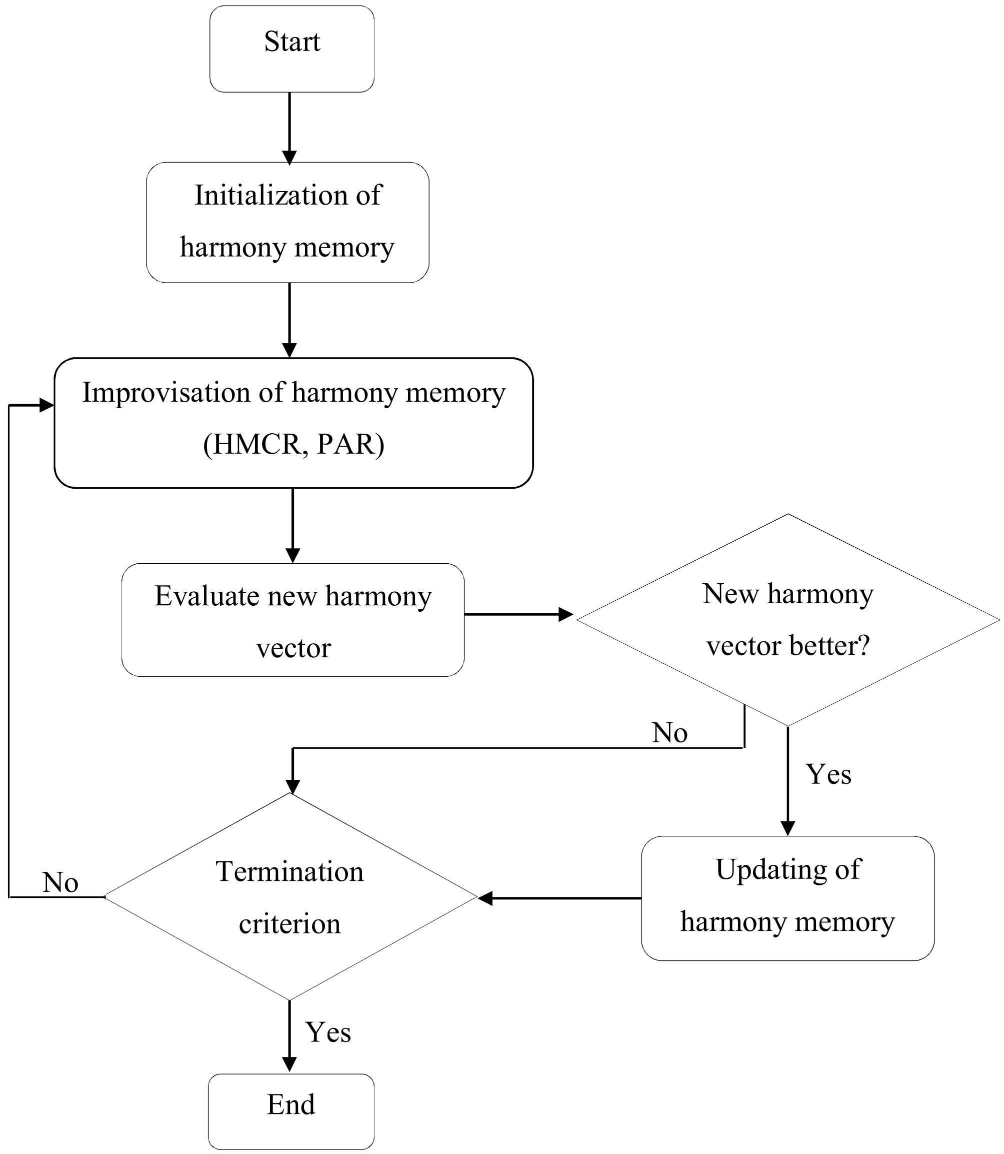

Figure 2.7: Flowchart of HS Algorithm

2.2.4.1 Parametric Study of HS

Harmony memory consideration in HS ensure the best harmonies will be brought forward to the new harmony memory. The exploitation function of harmony memory consideration is to choose the fit individual which is similar to GA. Therefore, a HMCR is assigned to effectively use this memory (Yang, 2009).

The second parameter of HS is pitch adjustment. The role of pitch adjustment in HS to produce a new memory characteristic is similar to mutation operator in GA to prevent the searching process being trapped in local space. Thus, PAR is assigned to monitor the degree of diversity of the solutions (Yang, 2014d).

PAR and randomization are likely to have similar role where it is functioning to diversify the solutions. However, PAR is limited to certain local pitch adjustment corresponds to a local search while the use of randomization will bring the system to explore globally (Yang, 2014d). The HMCR control the intensification factor in HS (Manjarres, et al., 2013). Higher value of HMCR will cause the system to converge faster, but the results obtained may not be the global optimum due to the harmonies are not explored well. On the other hand, lower value of HMCR will cause the system to converge slower due to lack of exploitation process. In summary, it is important that the value of parameter has to properly adjusted in order to increase the performance of HS in optimization.

2.2.4.2 Application of HS

The behaviour of HS in balancing between the intensification and diversification is depend on the parameters of HS (Manjarres, et al., 2013). Thus, the selection of parameter's value is relatively important for the system to obtain optimum solution. Lee, Han and Geem (2011) has demonstrate the effectiveness of the HS in optimizing twenty five bar space trusses. Variation of parameter's value as shown in Figure 2.8 has been applied in this optimization process to show which parameter's value can give the best optimum result. The optimal results obtained is shown in Figure 2.9.

Cases (1)	HMS (2)	HMCR (3)	PAR (4)
Case-1	20	0.9	0.45
Case-2	40	0.9	0.45
Case-3	30	0.9	0.4
Case-4	30	0.8	0.3
Case-5	30	0.9	0.3

Figure 2.8: The Value of HS Algorithm Parameters Used for Structural Optimization (Lee, et al., 2011)

Design variables A_i (in.^{2}) (1)		HS results Case-1 (2)	Case-2 (3)	Case-3 (4)	Case-4 (5)	Case-5 (6)	Rajeev *et al.* (1992) (7)	Wu & Chow (1995a) (8)	Wu & Chow (1995b) (9)	Adeli & Park (1996) (10)	Erbatur *et al.* (2000) (11)	Park & Sung (2002) (12)
1	A_1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.6	0.1	0.1
2	$A_2 \sim A_5$	0.6	0.3	0.3	0.5	0.3	1.8	0.6	0.5	1.4	1.2	2.1
3	$A_6 \sim A_9$	3.4	3.4	3.4	3.4	3.4	2.3	3.2	3.4	2.8	3.2	3.4
4	$A_{10} \sim$	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.5	0.1	0.1
5	A_{11}	1.6	2.1	2.1	1.9	2.1	0.1	1.5	1.5	0.6	1.1	2.2
6	$A_{12} \sim$	1.0	1.0	1.0	0.9	1.0	0.8	1.0	0.9	0.5	0.9	1.1
7	A_{13}	0.4	0.5	0.5	0.5	0.5	1.8	0.6	0.6	1.5	0.4	1.0
8	$A_{14} \sim$	3.4	3.4	3.4	3.4	3.4	3.0	3.4	3.4	3.0	3.4	3.0
	A_{17}											
	$A_{18} \sim$											
	A_{21}											
	$A_{22} \sim$											
	A_{25}											
Weight (lb)		485.77 [521.04][a]	484.85 [504.72][a]	484.85 [514.20][a]	485.05 [514.21][a]	484.85 [504.28][a]	546.01	491.72	486.29	543.95	493.80	537.23
Number of structural analyses		13,736 [13,445][b]	14,163 [4,414][b]	13,523 [2,160][b]	17,159 [5,226][b]	18,734 [6,850][b]	600	-	40,000	-	-	-

[a] The HS optimal results obtained after 600 structural analyses (the result of Rajeev and Krishnamoorthy, 1992).
[b] Number of analyses for the HS required to obtain a weight of 486.29 lb (the result of Wu and Chow, 1995b).

Figure 2.9: The Optimal Results of Twenty Five Bar Space Truss with Other Optimization Methods (Lee, et al., 2011)

Based on the optimal result obtained shown in Figure 2.9, the selection of parameter’s value in Case 3 give the least structural weight with 484.85 lb. Although the selection of HS parameter’s value is not the optimum, however, it is still giving a lighter structural weight compare to other optimization methods. Thus, HS is a strong optimization method for finding the optimum structure with discrete sizing variables (Lee, et al., 2011).

In this context, HS algorithm will be used as the optimization method to perform topology optimization of truss. HS algorithm is chosen to be used as the optimization method due to its simple implementation of HS algorithm (Yang, 2009). Comparing to conventional mathematical approach in optimization, HS algorithm require lesser mathematical calculation and the quality of solutions will not influenced by initial decision of design variables (Lee and Geem, 2005). Besides, HS algorithm generate a new harmony vector by considering all the existing vector in harmony memory based on HMS, HMCR and PAR. Therefore, this three parameters of HS provide flexibility in handling the exploitation and exploration process of the algorithm to give a better solution (Lee and Geem, 2005). Harmony memory and pitch adjustment make sure that best local solutions are retained while randomization allow the system to explore the search space globally. Thus, the combination of harmony memory, pitch adjustment and randomization controlled the diversification and intensification around the good solutions causes high efficiency of HS algorithm in obtaining approximately optimal solutions (Yang, 2009).

2.3 Summary

The traditional mathematical optimization methods are mostly gradient-based and derivative-based. The gradient-based methods allow the system to converge faster, but it is inefficient in discontinuous problems. Furthermore, multiple peaks of objective function and constraints cause the gradient search method to be difficult and ineffective. In addition, the traditional mathematical optimization methods are affected by the selection of initial points when there is more than one local optimum for a given optimization problem. This causes the optimal result obtained using traditional mathematical optimization methods may not be the global optimum. In real world situation, the structural optimization problems are mostly discrete and high complexity. Therefore, meta-heuristics algorithms is the best optimization tools to solve engineering optimization problems to overcome the computational drawbacks of mathematical algorithms (Jaberipour and Khorram, 2010).

GA is inspired by biological evolution. Each of the individual in GA is represented by a random discrete design variable. The individual in GA is encoded in the form of chromosome. Selection, crossover and mutation are the key elements in GA to produce new offspring among the population. The generation of new offspring follows Darwinian survival of the fittest theory in which the individual with higher fitness value will be retained while lower fitness value will be eliminated. The selection of two of the existing fitter individuals to generate a new offspring without considering every each of the individual in a population will lead GA to converge prematurely.

SA mimic the annealing process of a metal. In the annealing process, a high energy state of a metal is left to cool down slowly at careful control of the temperature until the minimum energy is achieved. This annealing process of the metal can be simulated to solve optimization problems. There are some disadvantages using SA algorithm in optimizing engineering problems. The system is slow in converging toward optimum solution due to high initial solution that required large number of function evaluations. In addition, SA algorithm is relatively weak in exploitation process which cause the computational time longer.

Swarm intelligence mimics the social behaviour of animals such as bird flocking. The optimization process of using PSO is analogous to a flock of birds seek for food sources randomly and find the best food source through communication among the flock while ACO is analogous to the foraging behaviour of real ants. The drawbacks of using PSO algorithm in optimization problems is that PSO and ACO having difficulties in providing a balance between exploration and exploitation process which will affect the optimal solution obtained. Besides, the use of strongly selective global best solution that speed up the convergence toward the optimum solution will cause premature convergence to occur.

HS is an optimization method that simulate the musical process. The optimization procedures are similar to a musician that search for a perfect state of harmony for achieving aesthetic standard of music. The implementation of HS algorithm is easier such that the decision of choosing initial values of design variables will not influence the quality of the solutions obtained (Yang, 2009). The summary of the main features for GA, SA, PSO, ACO and HS are tabulated in Table 2.2.

Table 2.2: Main Features of the Optimization Algorithms

	GA	SA	PSO	ACO	HS
Initial Design	Random population	Random designs	Random swarm	Assigned by probability function	Random harmony memory matrix
Intensification	Individual with higher fitness have mating opportunity	Better solution always accepted	Best particle's position guides all other particles to follow the best particle	Pheromone deposited based on the value of objective function	Based on HMCR that new HM matrix is generated from existing HM
Diversification	Crossover and mutation operators	Allow acceptance of worse design	Velocity of the particles	Probability function that allow worse design to be assigned	HMCR allow random design and PAR allow mutation
Acceptance	Stronger than current individuals	Better than current design	New best position accepted	Higher pheromone concentration than current path	Better than worst member is HM
Termination	Max iterations	Max iterations	Max iterations	Max iterations	Max iterations

All the popular meta-heuristic algorithm mentioned above are widely used in solving optimization problems. HS algorithm is a powerful optimization tool due to its robustness and effectiveness in generating global optimum result within a reasonable time (Geem, et al., 2001). Compared to GA, HS produce a new solution vector after considering all the values in the harmony memory matrix which allows HS to achieve a better global optimum solution. HS parameters such as randomization is similar to exploration process while HMCR and PAR exploit the information toward a good local optimum allows the system to perform structural optimization effectively. In view of this, HS is selected as the optimization method of truss topology in this study.

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this study, the initial layout of a truss structure is initialized using ground structure method where the possible connectivity of truss elements among the nodes are initially generated. The finite element method is used to perform truss analysis to determine element stresses and nodal displacements. Next, Harmony Search (HS) act as optimization algorithm that optimize the truss structure in terms of their connectivity and element cross-sectional areas with an objective to minimized the weight of truss that satisfied the constraints defined by user such as allowable displacement and yield stress.

3.2 Ground Structure Method

In ground structure method, the design domain is divided into a grid of nodal points with the union of all potential bars that are interconnected between the nodes (Zhao, 2014). A suitable ground structure that use for truss topology optimization can be determined by referring a graph theory which was introduced by Kaveh and Kalatjari (2003) as shown in Figure 3.1.

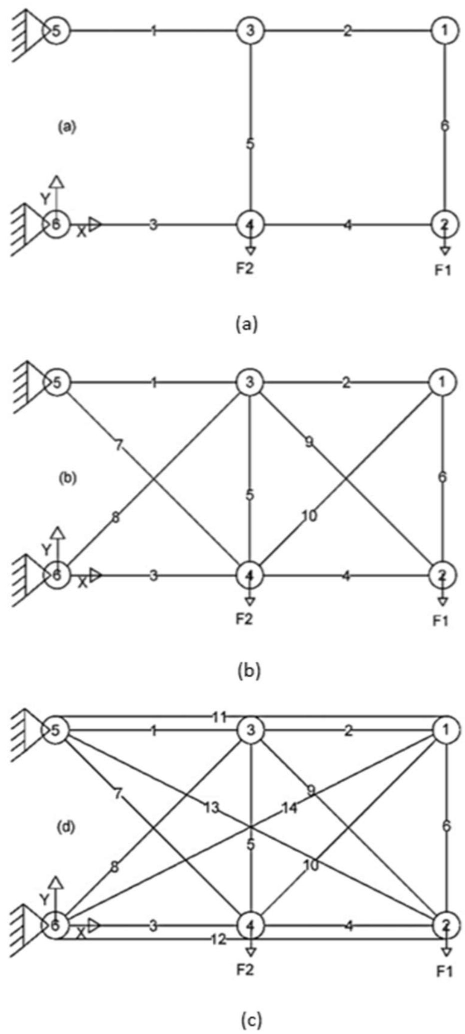

Figure 3.1: Graph Theory (Kaveh and Kalatjari, 2003)

A truss with minimum members as shown in Figure 3.1(a) is known as simple graph based ground structure. A truss with all pairs of nodes are connected by single member as shown in Figure 3.1(c) is known as complete graph based ground structure. A star graph based ground structure as shown in Figure 3.1(b) is a ground structure where all the nodes are connected to the neighbouring nodes only. The selection of ground structure to perform truss topology optimization is important because this will affect the time needed to obtain the optimal structure and constructability of the optimal structure. For instance, if there are too many members in ground structure, this will increase the complexity of the structural optimization problem and require high computational effort which will eventually result in high computational time. Thus, an appropriate ground structure must be chosen to perform structural topology optimization so that a practical design of truss structure can be obtained and the amount of the computational time can be reduced.

In this study, a star graph based ground structure is selected to perform truss topology optimization. This is because star graph based ground structure provide more flexibility in the design of truss topology and the number of members in ground structure is not complex as complete graph based ground structure.

3.3 Finite Element Method

Finite element method was developed initially as matrix method to perform structural analysis for truss (Tejani, 2018). It calculates the strength and behaviour of the truss structure. A truss element as shown in Figure 3.2 can be considered as a line element with simply supported end. The truss bar is connected between two nodes and each node has two degree of freedom corresponding to two directions displacement which are divided into x and y-direction. Assume an element of a truss length of L, cross-sectional area, A and modulus of elasticity or known as Young's modulus, E. The truss element is subjected to applied loads and boundary conditions. The equation of finite element analysis is represented in Eq. (3.1), where K represents the stiffness matrix; δ represents the displacement vector and F represents the force vector. This equation can conveniently assemble in matrix form as shown in Eq. (3.2).

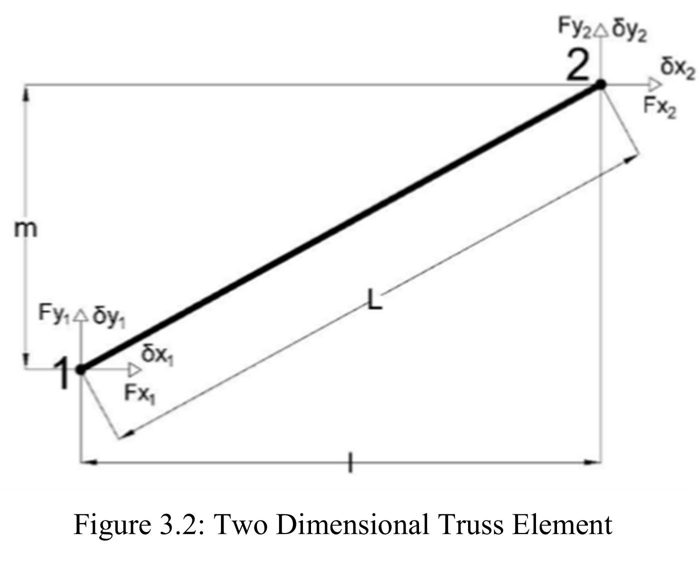

Figure 3.2: Two Dimensional Truss Element

$$[F] = [K][\delta] \tag{3.1}$$

$$\begin{bmatrix} F_{x_1} \\ F_{y_1} \\ F_{x_2} \\ F_{y_2} \end{bmatrix} = \frac{AE}{L} \begin{bmatrix} l^2 & lm & -l^2 & -lm \\ lm & m^2 & -lm & -m^2 \\ -l^2 & -lm & l^2 & lm \\ -lm & -m^2 & lm & m^2 \end{bmatrix} \begin{bmatrix} \delta_{x_1} \\ \delta_{y_1} \\ \delta_{x_2} \\ \delta_{y_2} \end{bmatrix} \tag{3.2}$$

The stress of the truss element is represented as shown in Eq. (3.3).

$$\sigma = \frac{E}{L} \begin{bmatrix} -l & -m & l & m \end{bmatrix} \begin{bmatrix} \delta_{x_1} \\ \delta_{y_1} \\ \delta_{x_2} \\ \delta_{y_2} \end{bmatrix} \tag{3.3}$$

By using this finite element method, the primary unknowns are nodal displacements. These unknowns can be obtained by multiplication of the inverse of the stiffness matrix with the force vector. With the obtained nodal displacement, the stress of the truss element can be calculated. In this research, ground structure method and restructuring of finite element model are used together to perform a single-stage optimization design strategy.

3.4 Optimization Procedure of Truss Topology

The objective of truss topology optimization is to find the best connectivity between the structural members to form a truss structure with minimum weight. Figure 3.3 shows a flowchart to illustrate the procedure in obtaining an optimal truss structure. A brief optimization steps using ground structure method, finite element method and Harmony Search (HS) to find the best truss topology and sizing are indicated as below.

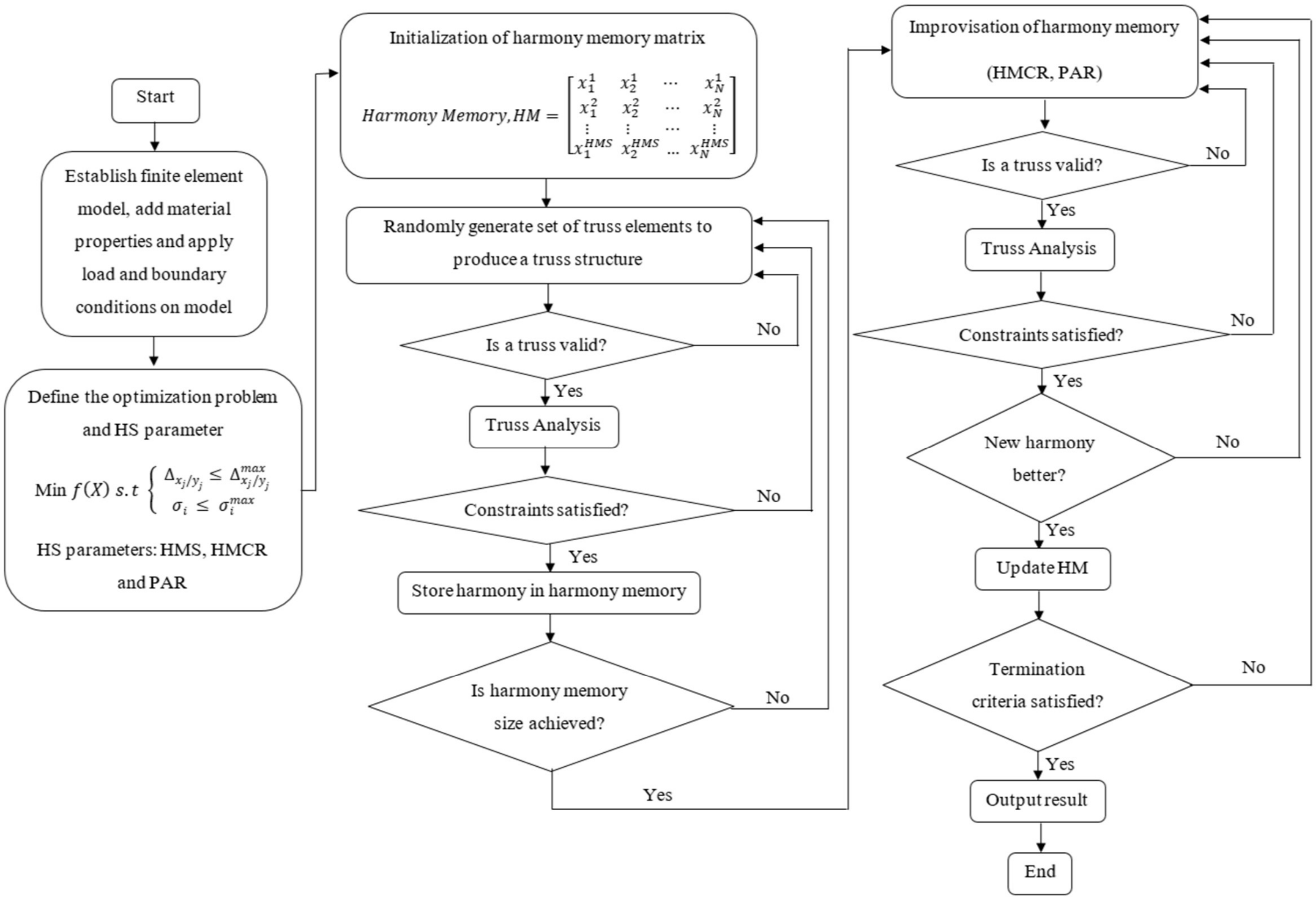

Figure 3.3: Truss Topology Optimization Flowchart Using HS

3.4.1 Step One: Define the Ground Structure of the Truss

Firstly, the design domain is divided into a grid of nodal points by inputting the number of truss elements for both x and y axes and the length of each element for respective axis. After the nodes are generated, all the nodes are connected with tentative truss element to the neighbouring nodes to form star graph based ground structure. The material property such as Young's modulus and the grade of steel are defined in this step. Besides, the location of loadings applied and boundary conditions are also assigned at this step.

3.4.2 Step Two: Define Structural Optimization Problem and Harmony Search's (HS) Parameters

The structural optimization problem is defined as in Eq. (3.4), (3.5), (3.6) and (3.7).

$$Find\ X = \{x_i\}, i = 1, 2, 3 \ldots, N \tag{3.4}$$

$$Minimize\ mass\ of\ truss,\ f(X) = \sum_{i=1}^{N} 7850.2\ x_i\ L_i \tag{3.5}$$

Subjected to:

$$g_1(X) : Displacement\ Constraints,\quad \delta_{x_j/y_j} \leq \delta_{x_j/y_j}^{max} \tag{3.6}$$

$$g_2(X) : Stress\ Constraints,\quad \sigma_i \leq \sigma_i^{max} \tag{3.7}$$

where $i = 1, 2, 3 \ldots, N$; $j = 1, 2, 3 \ldots, M$

Where, x_i, L_i, σ_i stand for cross-sectional area, element length, stress on the element 'i' respectively. δ_{x_j/y_j} is the value of nodal displacement of node 'j' respectively, where x, y indicate x and y axis respectively. Superscripts 'max' indicate maximum allowable limit.

Based on the constant value of 7850.2 from Eq. (3.5), it is obtained from the relationship between the weight per unit length, kg/m of truss element and its cross-sectional area provided by MELEWAR STEEL TUBE SDN. BHD's product catalogue as shown in APPENDIX A. Figure 3.4 shows a density of 7850.2 kg/m^3 that used to determine the mass of truss structure.

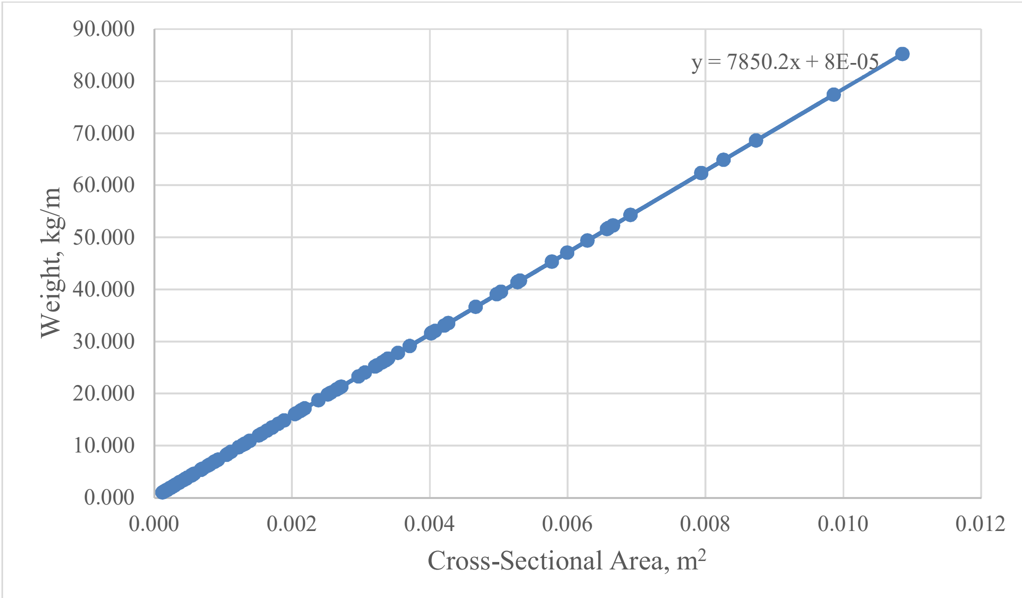

Figure 3.4: Graph of Weight per Unit Length against Cross-Sectional Area

In addition, the HS parameters defined at this step are: Harmony Memory Size (HMS), Harmony Memory Considering Rate (HMCR), Pitch Adjusting Rate (PAR), and the maximum number of iterations as termination criteria for the system. In this study, the value of HMS, HMCR, PAR and maximum number of iterations used to perform structural optimization are 20, 0.68, 0.3 and 1000 respectively.

3.4.3 Step Three: Randomly Generate Set of Truss Elements and Check the Validity of the Truss Structure

Once a set of truss elements are generated, the truss is subjected to check on its kinematic stability by calculating the degree of freedom (DOF) of the truss as shown in Eq. (3.8).

$$DOF = b + r - 2j \tag{3.8}$$

where b = numbers of elements;

r = restricted number of degrees of freedom at support nodes;

j = number of nodes

If the DOF is a non-positive value, the truss structure is found to be statically indeterminate, the truss structure is consider invalid and will not be used for the truss analysis. Besides, the truss structure is also invalid when there is no element connected to supports or nodes subjected to applied load. Once a valid truss structure is generated, this set of truss elements will proceed to truss analysis.

3.4.4 Step Four: Truss Analysis

A valid truss structure will be analysed using finite element method. At this step, a force vector and global stiffness matrix of the truss are computed. Since truss topology optimization involved removing or maintaining the truss element until the best connection of structural members is found, this process will cause a global stiffness matrix to become singular, meaning that an optimization may fail before reaching the optimal solution. Therefore, a significantly small value of 0.000000001 m^2 is assigned for the cross-sectional value of those removed elements to avoid singularity problem.

After the global stiffness matrix and force vector are computed, the unknown displacement vector can be determined using Eq. (3.1) to calculate the stresses.

3.4.5 Step Five: Constraints Checking

In this study, the constraints are set to a value of 10 mm and 235 MPa for nodal displacements and yielding stress respectively. If the constraints are satisfied, this set of truss elements will be stored in harmony memory as shown in Eq. (3.9) and the mass of the truss structure is computed. If any one of the constraint is not satisfied, the truss is invalid and step three need to be repeated. Step three to step five is the initialization of harmony memory and it is repeated until the harmony memory size is achieved.

$$Harmony\ Memory, HM = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_N^2 \\ \vdots & \vdots & \cdots & \vdots \\ x_1^{HMS} & x_2^{HMS} & \dots & x_N^{HMS} \end{bmatrix} \tag{3.9}$$

3.4.6 Step Six: Improvisation of Harmony Memory

A new harmony vector, $x' = [x'_1, x'_2, \cdots x'_N]$ is generated to produce a new harmony memory based on the Harmony Memory Considering Rate (HMCR), Pitch Adjustment Rate (PAR) and randomization. HMCR is the probability that the system will select the value store in the harmony memory while (1 - HMCR) is the probability that the system will randomly choose the possible range of design variable not limited to the value that stored in harmony memory. For instance, the first decision variable that used to form a new harmony vector, x'_1 is selected from any discrete value in the HM such that $x'_1 = [x_1^1, x_1^2, \cdots, x_1^{HMS}]$ based on the defined value of HMCR which is 0.68 or randomly select the entire cross-sectional area of the steel section such that $x'_1 \in X$ based on the value of (1-HMCR). Other design variables used to form a new harmony vector are in the same manner.

$$x'_i \leftarrow \begin{Bmatrix} x'_i \in \{x_i^1, x_i^2, \cdots, x_i^{HMS}\} \; with\; probability\; HMCR \\ x'_i \in X \; with\; probability\; (1 - HMCR) \end{Bmatrix} \tag{3.10}$$

Any value that chosen from HM for improvisation of HM is then determined by the PAR for pitch adjustment as shown in Eq. (3.11).

$$Pitch\; adjusting\; decision, x'_i \leftarrow \begin{Bmatrix} "Yes" \; with\; probability\; PAR \\ "No" \; with\; probability\; (1 - PAR) \end{Bmatrix} \tag{3.11}$$

Pitch adjustment is carried out when a value is chosen from HM for improvisation. PAR is the probability that the system will take the neighbouring value of the value that extract from HM while (1 – PAR) is the probability that the system will not do any pitch adjusting on the value that chosen from HM to form a new vector. In this study, a defined value of 0.3 for PAR means that the system will select a neighbouring value of 30% × HMCR probability while the system will do nothing on the value of (100% − 30%) × HMCR probability. If the system decides to do pitch adjustment on a value, then the x'_i will be replaced with $x_i(K^{th})$ and becomes

$$x'_i \leftarrow x_i(K^{th} \pm 1) \tag{3.12}$$

The probability for the system to pick a neighbour value to improvise a new harmony $x_i' \leftarrow x_i(K^{th}+1)$ or $x_i' \leftarrow x_i(K^{th}-1)$ is the same.

If a newly generated harmony vector, x' satisfied the constraints specified, it will proceed to the following step. Else, the improvisation process is repeated until a new harmony vector that satisfied the constraints is found.

3.4.7 Step Seven: Revision of Harmony Memory

The mass of a newly generated set of truss elements is computed. If the new mass is lower than the largest weight that determine from existing harmony memory, this set of truss elements that contribute to the largest weight will be eliminated and replace with the newly generated set of truss elements.

3.4.8 Step Eight: Check the Termination Criteria

At this step, the algorithm will check whether the optimization process reach the maximum number of iterations. If the termination criteria not satisfied, the optimization process will be repeated from step six until the termination criteria is satisfied.

3.4.9 Step Nine: Output of Optimal Result

When the maximum number of iterations is achieved, the best topology and cross-sectional areas of the truss elements that give minimum weight of the truss structure obtained from the harmony memory are generated.

3.5 Model Development

A star graph based ground structure of six structural members as shown in Figure 3.6 was generated with the user's input as shown in Figure 3.5. This truss structure is then optimized to obtain the best topology and sizing with the operating steps mentioned above.

```
Number of x element = 1
Number of y element = 1
Interval in x-direction = 6
Interval in y-direction = 3

**Harmony Search Parameters**
Harmony Memory Size = 30
Maximum Iteration = 800
Harmony Memory Considering Rate = 0.68
Pitch Adjustment Rate = 0.3

Cold Formed Circular Hollow Section Steel Properties
Specification: BS EN 10219:2006

Grade = S235/S275/S355
What Grade? --> S235
Yield Stress = 235,000 kN/m2
```

Figure 3.5: User's Input to Generate a Six Members Truss Structure

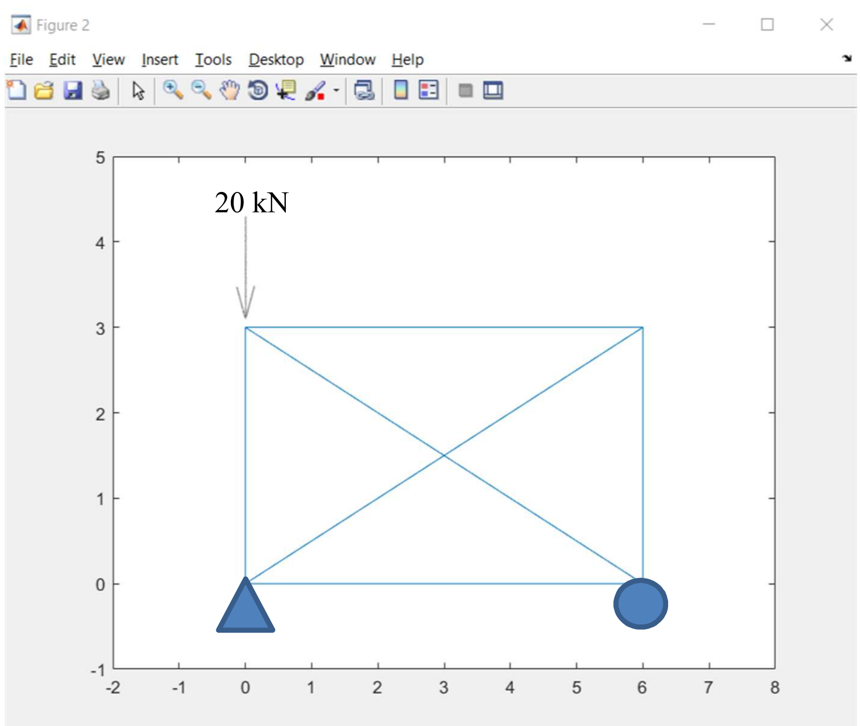

Figure 3.6: Six Members Ground Structure Truss Before Optimization

An optimal truss topology of six members ground structure truss as shown in Figure 3.7 shows that the optimization procedures mentioned above works well in obtaining the best connectivity between the truss elements to produce a truss structure with minimum weight.

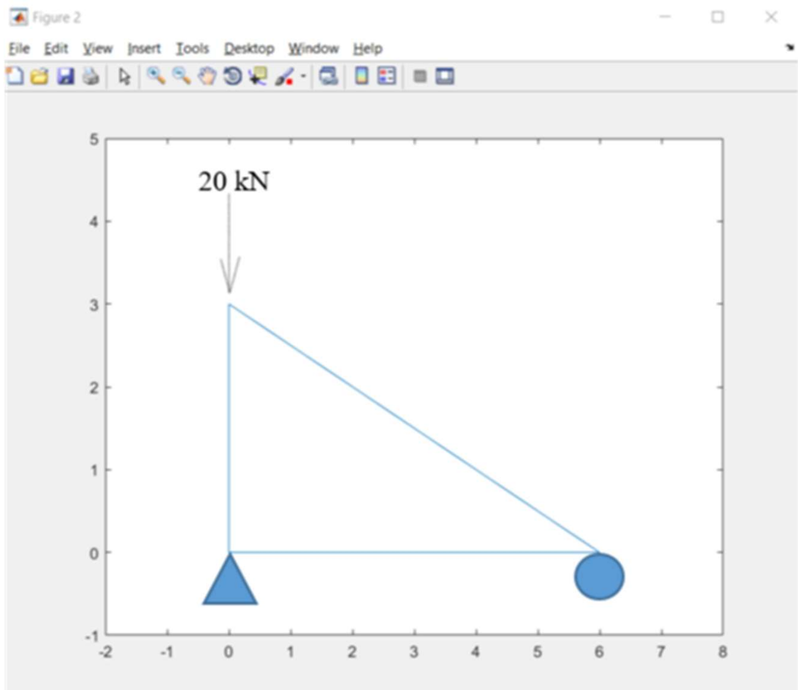

Figure 3.7: Optimal Truss Structure of Six Members Ground Structure After Optimization

3.6 Summary

In summary, a finite element model is first established with all the information given such as material properties, location of the load applied and boundary conditions. Next, the objective function of the structural optimization problem and all the HS's parameters such as HMS, HMCR, PAR and the numbers of maximum iterations are defined to perform the optimization using MATLAB software. In the optimization process, it starts with initialization of harmony memory matrix followed by improvisation of harmony memory until the termination criteria is satisfied. Finite element method is involved in the optimization process to ensure that the improvised truss structure satisfy all the constraints. With the proposed methodology in performing truss topology optimization, a best truss topology satisfying all the constraints i.e., nodal displacements and yielding stress is able to be determined.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

The proposed methodology developed by Harmony Search (HS) algorithm is used to perform truss topology optimization to generate the best layout of truss structure and its cross-sectional area. In addition, the proposed methodology also generate the result of nodal displacements and element stresses based on the location and the amount of load applied on the ground structure truss.

The optimal layout of the truss structure and cross-sectional area of the structural members generated from HS are then applied in a structural analysis and design software which is SCIA Engineer to do the comparison of the results in nodal displacements and element stresses.

In this chapter, the results for eleven elements, sixteen elements and twenty-one elements ground structure truss that generated from HS are compared with the SCIA Engineer to validate the optimal truss structure obtained from the proposed methodology. Next, the discussion on accuracy of the results obtained from HS is discussed. Lastly, the simulation time for the topology optimization of truss structure using the proposed methodology is discussed.

4.2 Validation

The purpose of validation is to ensure the optimal solution obtained from the proposed methodology is feasible and reliable. In this study, the truss topology optimization of eleven, sixteen and twenty-one elements ground structure trusses are performed with several loading conditions. The validation of the optimal solutions obtained from HS will be discussed as below:

4.2.1 Validation of the Eleven Elements Ground Structure Truss

For the validation of eleven elements ground structure truss, the load is applied at the middle top node as highlighted in Figure 4.1 to determine an optimal truss topology. The eleven elements ground structure truss subjected to load applied at the middle top node is optimized to generate an optimal truss structure containing six elements as shown in Figure 4.2. Figure 4.3 shows the model generated from SCIA Engineer with the naming of elements and nodes to provide a clearer presentation of results. The best element cross-sectional areas for the optimal truss structure are tabulated in Table 4.1. The nodal displacements and element stresses of the optimal structure obtained from the proposed methodology and SCIA Engineer are tabulated in Table 4.2 and Table 4.3 respectively.

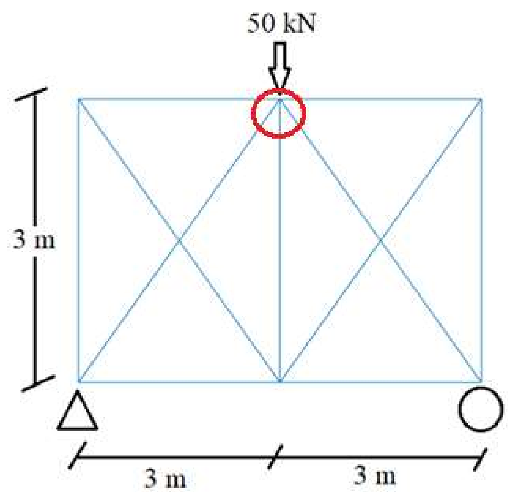

Figure 4.1: Ground Structure of Eleven Elements Truss

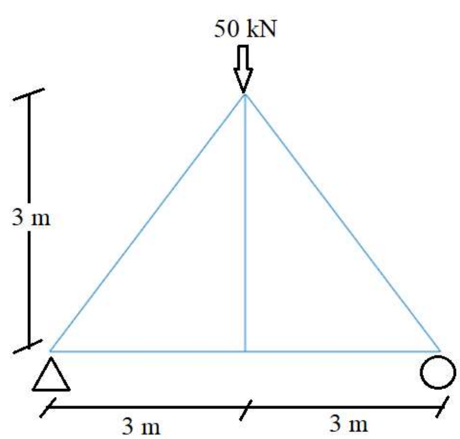

Figure 4.2: Optimal Truss Structure of Eleven Elements Truss

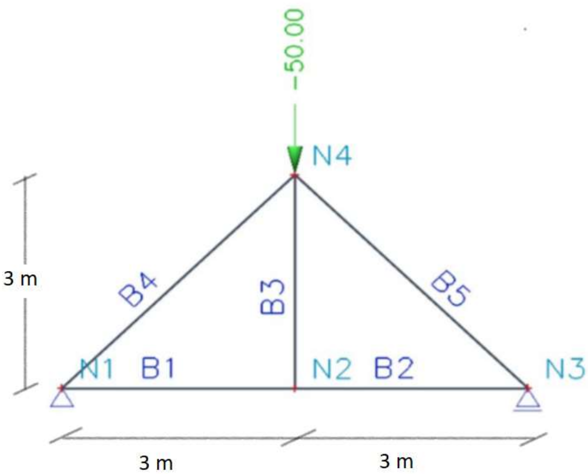

Figure 4.3: Optimal Truss Structure of Eleven Elements Truss with Naming of Nodes and Elements

Table 4.1: The Best Cross-Sectional Area of Optimal Truss Structure for Eleven Elements Truss

Element	Area (mm^2)	Length (mm)	Volume (mm^3)
B1	121.00	3000.00	363000.00
B2	121.00	3000.00	363000.00
B3	121.00	3000.00	363000.00
B4	156.00	4242.64	661851.95
B5	156.00	4242.64	661851.95
		Total Volume (mm^3)	2412703.89

Table 4.2: Nodal Displacements of Optimal Truss Structure for Eleven Elements Truss

Displacement of Nodes						
Node	**HS**		**SCIA**		**Accuracy**	
	x (mm)	**y (mm)**	**x (mm)**	**y (mm)**	**x (%)**	**y (%)**
N1	0.0	0.0	0.0	0.0	100.0	100.0
N2	3.1	-9.9	2.9	-9.4	93.1	94.7
N3	6.2	0.0	5.9	0.0	95.0	100.0
N4	3.1	-9.9	2.9	-9.4	93.1	94.7

Table 4.3: Element Stresses of Optimal Truss Structure for Eleven Elements Truss

Elemental Stress			
Element	**HS Stress (MPa)**	**SCIA Stress (MPa)**	**Accuracy (%)**
B1	206.6	206.2	99.8
B2	206.6	206.2	99.8
B3	0.0	0.0	100.0
B4	-226.6	-226.0	99.7
B5	-226.6	-226.0	99.7

The best result for optimal truss structure of eleven elements truss with load applied at middle top node reported for the respective nodal coordinates are node N1 (0, 0), node N2 (3, 0), node N3 (6, 0) and node N4 (3, 3) in metre. Based on Table 4.1, the total volume of the optimal truss structure is 2412703.89 mm^3 which is equivalent to 2.41E-3 m^3. The weight of the optimal truss structure for eleven elements truss is obtained from the product of density which is 7850.2 kg/m^3 with the total volume of the truss structure which give 18.94 kg.

Based on Table 4.2 and Table 4.3, the lowest percentage of accuracy for the displacement of node and elemental stress are 93.1% and 99.7% respectively. The maximum displacement of nodes obtained using the proposed methodology are 9.9 mm downward for both nodes which are N3 and N4, while for SCIA Engineer is 9.4 mm. The maximum element stresses obtained using the proposed methodology are 226.6 MPa in compression for both elements which are B4 and B5 while for SCIA Engineer is 226 MPa which is just 0.3% different in value.

Since SCIA Engineer able to give output by applying the optimal layout of truss structure generated from the proposed methodology, this shows that the topology obtained from the proposed methodology is feasible. Besides, the accuracy of the results obtained using the proposed methodology are above 90% which can be considered sufficient enough. Thus, the optimal solution obtained from the proposed methodology for eleven elements ground structure truss is validated.

4.2.2 Validation of the Sixteen Elements Ground Structure Truss

For the validation of sixteen elements ground structure truss, there are two load cases applied to determine the respective optimal truss topology. The load is applied at the second top node as highlighted in Figure 4.4 for the first load case. For the second load case, the load is applied at the third top node as highlighted in Figure 4.7. The optimal results obtained from the proposed methodology for the sixteen elements ground structure truss are presented with first load case followed by second load case.

First load case:

The sixteen elements ground structure truss subjected to first load case is optimized to generate an optimal truss structure containing nine elements as shown in Figure 4.5. Figure 4.6 shows the model generated from SCIA Engineer with the naming of elements and nodes to provide a clearer presentation of results. The best element cross-sectional areas for the optimal truss of sixteen elements truss subjected to first load case are tabulated in Table 4.4. The nodal displacements and element stresses of the optimal structure obtained from the proposed methodology and SCIA Engineer are tabulated in Table 4.5 and Table 4.6 respectively.

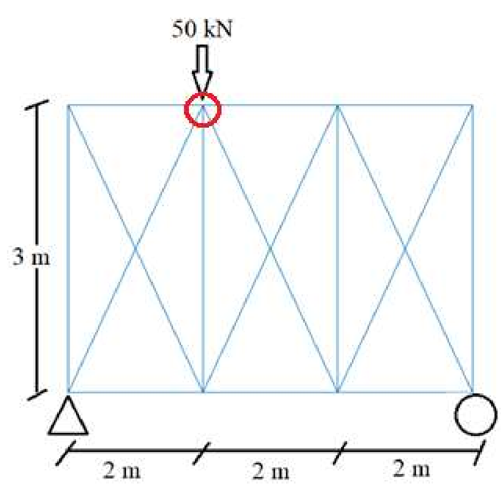

Figure 4.4: Ground Structure of Sixteen Elements Truss Subjected to First Load Case

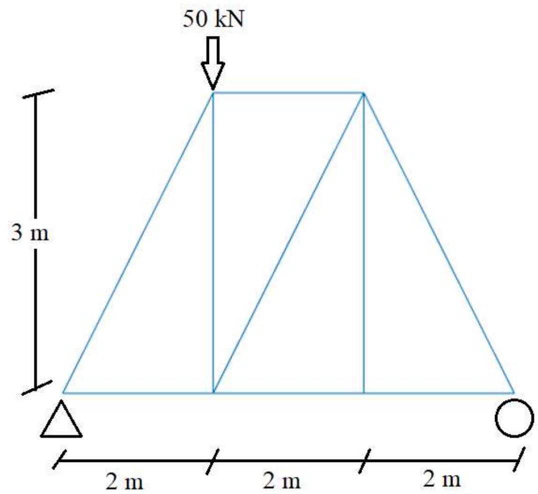

Figure 4.5: Optimal Truss Structure of Sixteen Elements Truss Subjected to First Load Case

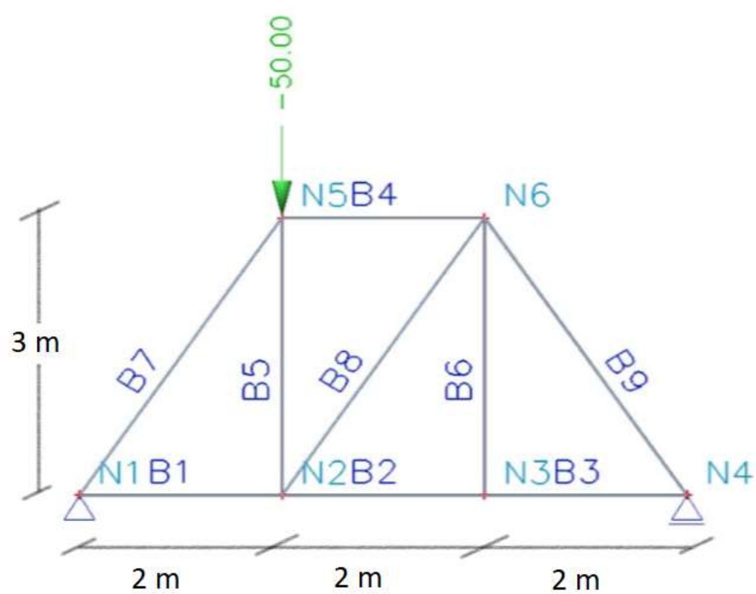

Figure 4.6: Optimal Truss Structure of Sixteen Elements Truss Subjected to First Load Case with Naming of Nodes and Elements

Table 4.4: The Best Cross-Sectional Areas of Optimal Truss Structure for Sixteen Elements Truss Subjected to First Load Case

Element	Area (mm^2)	Length (mm)	Volume (mm^3)
B1	121.00	2000.00	242000.00
B2	121.00	2000.00	242000.00
B3	121.00	2000.00	242000.00
B4	148.00	2000.00	296000.00
B5	121.00	3000.00	363000.00
B6	121.00	3000.00	363000.00
B7	172.00	3605.55	620154.82
B8	172.00	3605.55	620154.82
B9	121.00	3605.55	436271.70
		Total Volume (mm^3)	3424581.34

Table 4.5: Nodal Displacements of Optimal Truss Structure for Sixteen Elements Truss Subjected to First Load Case

Displacement of Nodes						
Node	**HS**		**SCIA**		**Accuracy**	
	x (mm)	**y (mm)**	**x (mm)**	**y (mm)**	**x (%)**	**y (%)**
N1	0.0	0.0	0.0	0.0	100.0	100.0
N2	1.8	-5.9	1.7	-5.6	92.0	94.4
N3	2.8	-4.1	2.6	-3.9	94.1	94.8
N4	3.7	0.0	3.5	0.0	95.1	100.0
N5	4.4	-8.0	4.2	-7.6	95.2	95.0
N6	2.9	-4.1	2.8	-3.9	96.4	94.8

Table 4.6: Element Stresses of Optimal Truss Structure for Sixteen Elements Truss Subjected to First Load Case

Elemental Stress			
Element	**HS Stress (MPa)**	**SCIA Stress (MPa)**	**Accuracy (%)**
B1	183.7	183.3	99.8
B2	91.8	91.6	99.8
B3	91.8	91.6	99.8
B4	-150.1	-150.5	99.8
B5	-137.7	-137.4	99.8
B6	0.0	0.0	100.0
B7	-232.9	-232.2	99.7
B8	116.5	116.1	99.7
B9	-165.5	-165.2	99.8

The best result for optimal truss structure of sixteen elements truss subjected to first load case reported for the respective nodal coordinates are node N1 (0, 0), node N2 (2, 0), node N3 (4, 0), node N4 (6, 0), node N5 (2, 3) and node N6 (4, 3) in metre. Based on Table 4.4, the total volume of the optimal truss structure is 3424581.34 mm^3 which is equivalent to 3.42E-3 m^3. The weight of the optimal truss structure for sixteen elements truss subjected to first load case is obtained from the product of density which is 7850.2 kg/m^3 with the total volume of the truss structure which give 26.88 kg.

Based on Table 4.5 and Table 4.6, the lowest percentage of accuracy for the displacement of node and elemental stress are 92.0% and 99.7% respectively. The maximum displacement of nodes obtained from the proposed methodology is 8.0 mm downward at node N5, while for SCIA Engineer is 7.6 mm. The maximum elemental stress obtained from the proposed methodology is 232.9 MPa in compression at element B7 while for SCIA Engineer is 232.2 MPa which is just 0.3% different in value.

Since SCIA Engineer able to give output by applying the optimal layout of truss structure generated from the proposed methodology, this shows that the topology obtained from the proposed methodology is feasible. Besides, the accuracy of the results obtained from the proposed methodology are above 90% which can be considered sufficient enough. Thus, the optimal solution obtained from the proposed methodology for sixteen elements ground structure truss subjected to first load case is validated.

Second load case:

The sixteen elements ground structure truss subjected to second load case is optimized to generate an optimal truss structure containing nine elements as shown in Figure 4.8. Figure 4.9 shows the model generated from SCIA Engineer with the naming of elements and nodes to provide a clearer presentation of results. The best element cross-sectional areas for optimal truss structure of sixteen elements truss subjected to second load case are tabulated in Table 4.7. The nodal displacements and element stresses of the optimal structure obtained from the proposed methodology and SCIA Engineer are tabulated in Table 4.8 and Table 4.9 respectively.

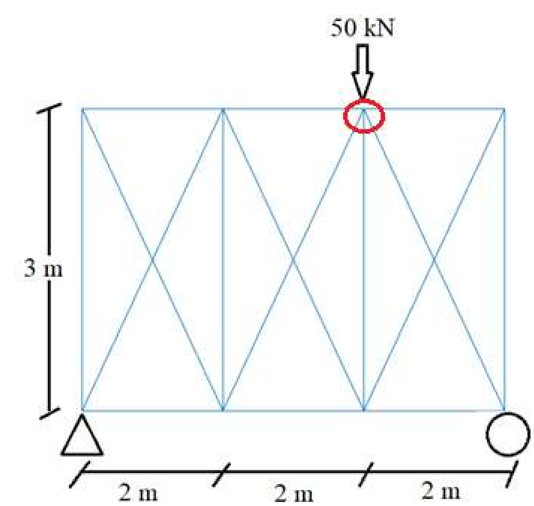

Figure 4.7: Ground Structure of Sixteen Elements Truss Subjected to Second Load Case

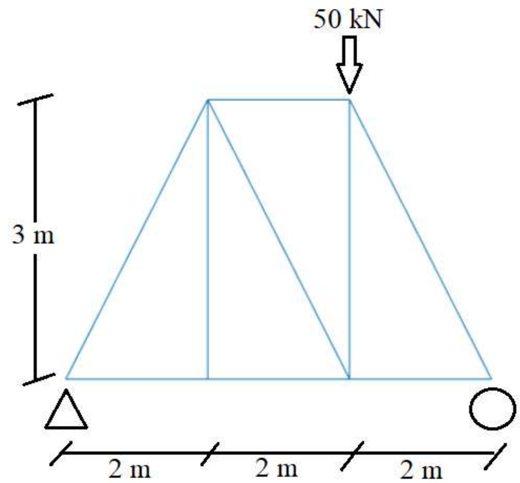

Figure 4.8: Optimal Truss Structure of Sixteen Elements Truss Subjected to Second Load Case

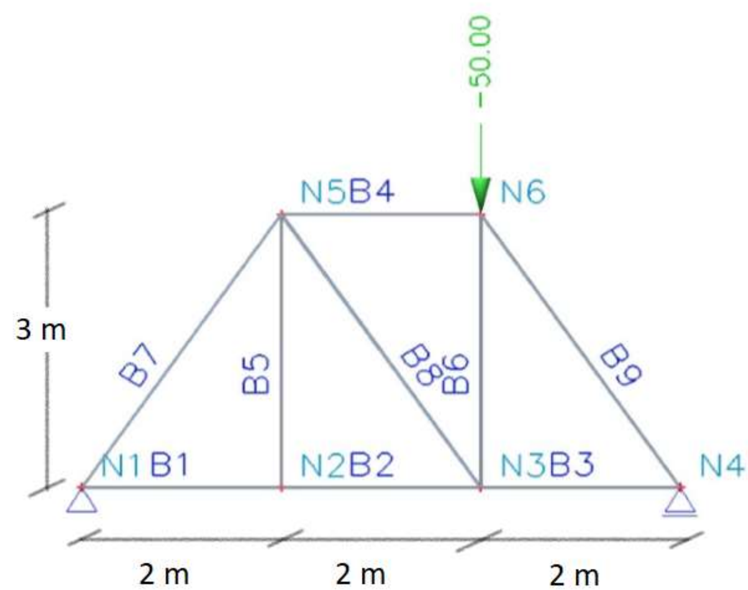

Figure 4.9: Optimal Truss Structure of Sixteen Elements Truss Subjected to Second Load Case with Naming of Nodes and Elements

Table 4.7: The Best Cross-Sectional Areas of Optimal Truss Structure for Sixteen Elements Truss Subjected to Second Load Case

Element	Area (mm^2)	Length (mm)	Volume (mm^3)
B1	121.00	2000.00	242000.00
B2	121.00	2000.00	242000.00
B3	121.00	2000.00	242000.00
B4	121.00	2000.00	242000.00
B5	121.00	3000.00	363000.00
B6	148.00	3000.00	444000.00
B7	121.00	3605.55	436271.70
B8	156.00	3605.55	562466.00
B9	172.00	3605.55	620154.82
		Total Volume (mm^3)	3393892.52

Table 4.8: Nodal Displacements of Optimal Truss Structure for Sixteen Elements Truss Subjected to Second Load Case

Displacement of Nodes						
Node	**HS**		**SCIA**		**Accuracy**	
	x (mm)	**y (mm)**	**x (mm)**	**y (mm)**	**x (%)**	**y (%)**
N1	0.0	0.0	0.0	0.0	100.0	100.0
N2	0.9	-4.2	0.9	-4.0	98.0	94.6
N3	1.8	-6.4	1.7	-6.1	92.0	95.1
N4	3.7	0.0	3.5	0.0	95.1	100.0
N5	0.9	-4.2	0.9	-4.0	95.2	94.6
N6	-0.9	-8.1	-0.9	-7.7	99.3	94.9

Table 4.9: Element Stresses of Optimal Truss Structure for Sixteen Elements Truss Subjected to Second Load Case

Elemental Stress			
Element	**HS Stress (MPa)**	**SCIA Stress (MPa)**	**Accuracy (%)**
B1	91.8	91.6	99.8
B2	91.8	91.6	99.8
B3	183.7	183.3	99.8
B4	-183.7	-183.3	99.8
B5	0.0	0.0	100.0
B6	-112.6	-112.9	99.7
B7	-165.5	-165.2	99.8
B8	128.4	128.0	99.7
B9	-232.9	-232.3	99.7

The best result for optimal truss structure of sixteen elements truss subjected to second load case reported for the respective nodal coordinates are node N1 (0, 0), node N2 (2, 0), node N3 (4, 0), node N4 (6, 0), node N5 (2, 3) and node N6 (4, 3) in metre. Based on Table 4.7, the total volume of the optimal truss structure is 3393892.52 mm^3 which is equivalent to 3.39E-3 m^3. The weight of the optimal truss structure for sixteen elements truss subjected to second load case is obtained from the product of density which is 7850.2 kg/m^3 with the total volume of the truss structure which give 26.64 kg.

Based on Table 4.8 and Table 4.9, the lowest percentage of accuracy for the displacement of node and elemental stress 92.0% and 99.7% respectively. The maximum displacement of nodes obtained using the proposed methodology is 8.1 mm downward at node N6, while for SCIA Engineer is 7.7 mm. The maximum elemental stress obtained from the proposed methodology is 232.9 MPa in compression at element B9 while for SCIA Engineer is 232.3 MPa which is just 0.3% different in value.

Since SCIA Engineer able to give output by applying the optimal layout of truss structure generated from the proposed methodology, this shows that the topology obtained from the proposed methodology is feasible. Besides, the accuracy of the results obtained using the proposed methodology are above 90% which can be considered sufficient enough. Thus, the optimal solution obtained from the proposed methodology for sixteen elements ground structure truss subjected to second load case is validated.

4.2.3 Validation of the Twenty-One Elements Ground Structure Truss

For the validation of twenty-one elements ground structure truss, there are three load cases applied to determine the respective optimal truss topology. In the first load case, the load is applied at the middle top node as highlighted in Figure 4.10. For the second load case, the load is applied at the second top node as highlighted in Figure 4.13 while for the third load case, the load is applied at the fourth top node as highlighted in Figure 4.16. The optimal results obtained for the twenty-one elements ground structure truss are presented with first load case, second load case and third load case.

First load case:

The twenty-one elements ground structure truss subjected to first load case is optimized to generate an optimal truss structure containing ten elements as shown in Figure 4.11. Figure 4.12 shows the model generated from SCIA Engineer with the naming of elements and nodes to provide a clearer presentation of results. The best element cross-sectional areas for optimal truss structure of twenty-one elements truss subjected to first load case are tabulated in Table 4.10. The nodal displacements and element stresses of the optimal structure obtained from the proposed methodology and SCIA Engineer are tabulated in Table 4.11 and Table 4.12 respectively.

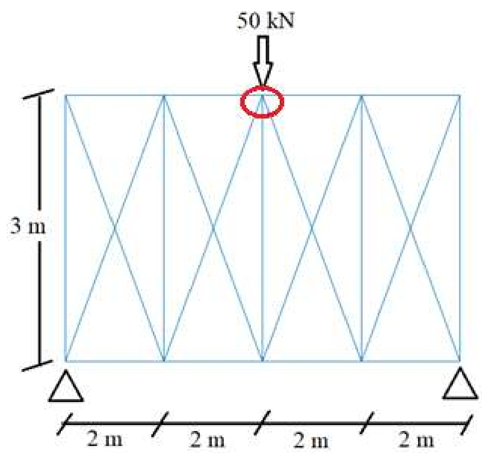

Figure 4.10: Ground Structure of Twenty-One Elements Truss Subjected to First Load Case

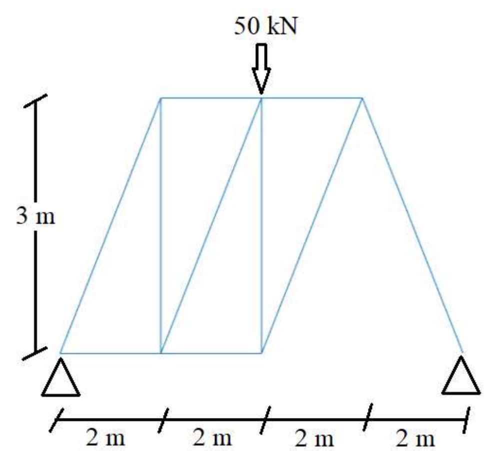

Figure 4.11: Optimal Truss Structure of Twenty-One Elements Truss Subjected to First Load Case

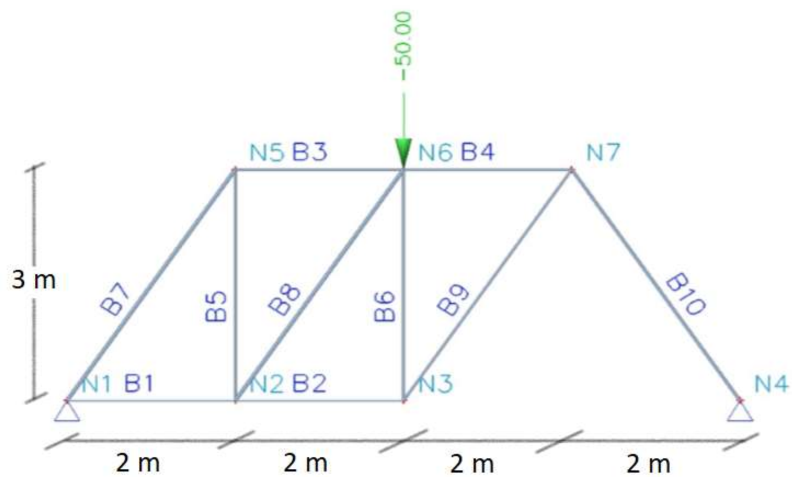

Figure 4.12: Optimal Truss Structure of Twenty-One Elements Truss Subjected to First Load Case with Naming of Nodes and Elements

Table 4.10: The Best Cross-Sectional Areas of Optimal Truss Structure for Twenty-One Elements Truss Subjected to First Load Case

Element	Area (mm^2)	Length (mm)	Volume (mm^3)
B1	121.00	2000.00	242000.00
B2	121.00	2000.00	242000.00
B3	121.00	2000.00	242000.00
B4	192.00	2000.00	384000.00
B5	172.00	3000.00	516000.00
B6	172.00	3000.00	516000.00
B7	254.00	3605.55	915810.02
B8	254.00	3605.55	915810.02
B9	225.00	3605.55	811249.04
B10	199.00	3605.55	717504.70
		Total Volume (mm^3)	5502373.79

Table 4.11: Nodal Displacements of Optimal Truss Structure for Twenty-One Elements Truss Subjected to First Load Case

Displacement of Nodes						
Node	**HS**		**SCIA**		**Accuracy**	
	x (mm)	**y (mm)**	**x (mm)**	**y (mm)**	**x (%)**	**y (%)**
N1	0.0	0.0	0.0	0.0	100.0	100.0
N2	0.0	-6.5	0.0	-6.2	100.0	95.2
N3	1.4	-7.7	1.3	-7.4	94.1	95.7
N4	0.0	0.0	0.0	0.0	100.0	100.0
N5	2.6	-4.3	2.5	-4.1	94.6	94.6
N6	1.3	-9.9	1.2	-9.4	95.2	94.7
N7	-0.5	-3.6	-0.5	-3.4	95.7	94.4

Table 4.12: Element Stresses of Optimal Truss Structure for Twenty-One Elements Truss Subjected to First Load Case

Elemental Stress			
Element	**HS**	**SCIA**	**Accuracy (%)**
	Stress (MPa)	**Stress (MPa)**	
B1	0.0	0.0	100.0
B2	137.7	137.4	99.8
B3	-137.7	-137.4	99.8
B4	-173.6	-173.9	99.8
B5	145.3	144.9	99.7
B6	-145.3	-144.9	99.7
B7	-118.3	-118.4	99.9
B8	-118.3	-118.4	99.9
B9	133.5	133.4	99.9
B10	-151.0	-150.9	99.9

The best result for optimal truss structure of twenty-one elements truss subjected to first load case reported for the respective nodal coordinates are node N1 (0, 0), node N2 (2, 0), node N3 (4, 0), node N4 (8, 0), node N5 (2, 3), node N6 (4, 3) and node N7 (6, 3) in metre. Based on Table 4.10, the total volume of the optimal truss structure is 5502373.79 mm^3 which is equivalent to 5.50E-3 m^3. The weight of the optimal truss structure for twenty-one elements truss subjected to first load case is obtained from the product of density which is 7850.2 kg/m^3 with the total volume of the truss structure which give 43.19 kg.

Based on Table 4.11 and Table 4.12, the lowest percentage of accuracy for the displacement of node and elemental stress are 94.1% and 99.7% respectively. The maximum displacement of nodes obtained from the proposed methodology is 9.9 mm downward at node N6, while for SCIA Engineer is 9.4 mm. The maximum elemental stress obtained from the proposed methodology is 173.6 MPa in compression at element B4 while for SCIA Engineer is 173.9 MPa which is just 0.2% different in value.

Since SCIA Engineer able to give output by applying the optimal layout of truss structure generated from the proposed methodology, this shows that the topology obtained from the proposed methodology is feasible. Besides, the accuracy of the results obtained from the proposed methodology are above 90% which can be considered sufficient enough. Thus, the optimal solution obtained from the proposed methodology for twenty-one elements ground structure truss subjected to first load case is validated.

Second load case:

The twenty-one elements ground structure truss subjected to second load case is optimized to generate an optimal truss structure containing ten elements as shown in Figure 4.14. Figure 4.15 shows the model generated from SCIA Engineer with the naming of elements and nodes to provide a clearer presentation of results. The best element cross-sectional areas for twenty-one elements truss subjected to second load case are tabulated in Table 4.13. The nodal displacements and element stresses of the optimal structure obtained from the proposed methodologies and SCIA Engineer are tabulated in Table 4.14 and Table 4.15 respectively.

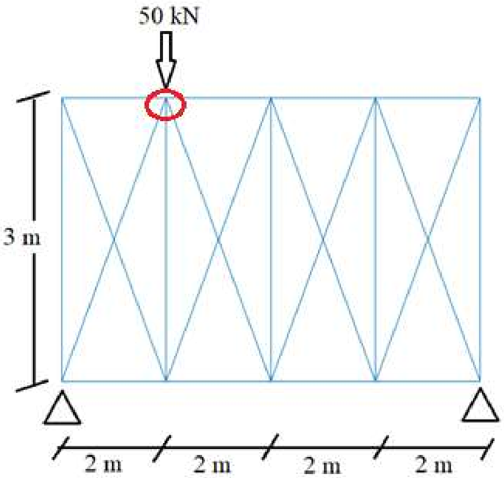

Figure 4.13: Ground Structure of Twenty-One Elements Truss Subjected to Second Load Case

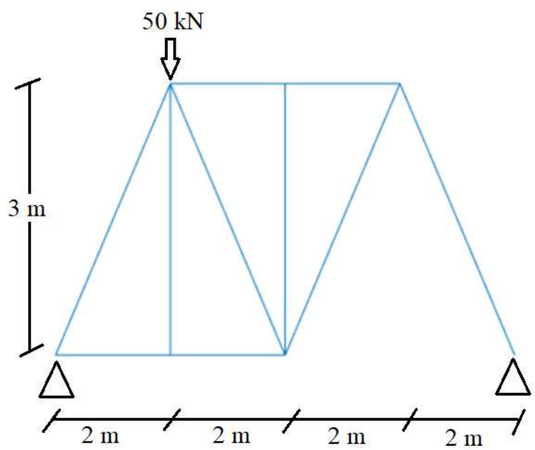

Figure 4.14: Optimal Truss Structure of Twenty-One Elements Truss Subjected to Second Load Case

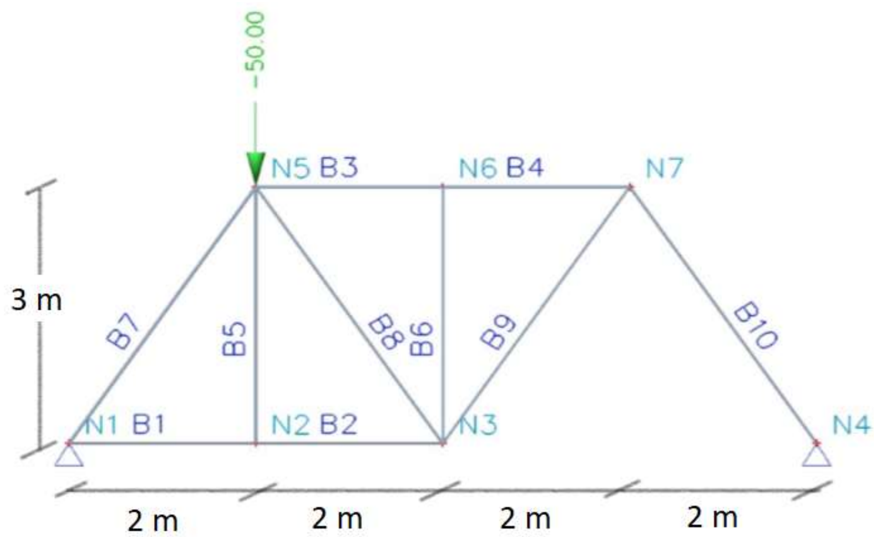

Figure 4.15: Optimal Truss Structure of Twenty-One Elements Truss Subjected to Second Load Case with Naming of Nodes and Elements

Table 4.13: The Best Cross-Sectional Areas of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Second Load Case

Element	Area (mm^2)	Length (mm)	Volume (mm^3)
B1	121.00	2000.00	242000.00
B2	121.00	2000.00	242000.00
B3	121.00	2000.00	242000.00
B4	121.00	2000.00	242000.00
B5	121.00	3000.00	363000.00
B6	121.00	3000.00	363000.00
B7	199.00	3605.55	717504.70
B8	121.00	3605.55	436271.70
B9	121.00	3605.55	436271.70
B10	121.00	3605.55	436271.70
		Total Volume (mm^3)	3720319.82

Table 4.14: Nodal Displacements of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Second Load Case

Displacement of Nodes						
Node	**HS**		**SCIA**		**Accuracy**	
	x (mm)	**y (mm)**	**x (mm)**	**y (mm)**	**x (%)**	**y (%)**
N1	0.0	0.0	0.0	0.0	100.0	100.0
N2	1.4	-7.5	1.3	-7.2	94.1	95.4
N3	2.8	-5.6	2.6	-5.4	94.1	95.7
N4	0.0	0.0	0.0	0.0	100.0	100.0
N5	3.9	-7.5	3.7	-7.2	93.5	95.4
N6	2.6	-5.6	2.4	-5.4	93.2	95.7
N7	1.2	-1.9	1.1	-1.8	92.2	94.5

Table 4.15: Element Stresses of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Second Load Case

Elemental Stress			
Element	**HS Stress (MPa)**	**SCIA Stress (MPa)**	**Accuracy (%)**
B1	137.7	137.4	99.8
B2	137.7	137.4	99.8
B3	-137.7	-137.4	99.8
B4	-137.7	-137.4	99.8
B5	0.0	0.0	100.0
B6	0.0	0.0	100.0
B7	-226.5	-226.3	99.9
B8	-124.2	-123.9	99.8
B9	124.2	123.9	99.8
B10	-124.2	-123.9	99.8

The best result for optimal truss structure of twenty-one elements truss subjected to second load case reported for the respective nodal coordinates are node N1 (0, 0), node N2 (2, 0), node N3 (4, 0), node N4 (8, 0), node N5 (2, 3), node N6 (4, 3) and node N7 (6, 3) in metre. Based on Table 4.13, the total volume of the optimal truss structure is 3720319.82 mm^3 which is equivalent to 3.72E-3 m^3. The weight of the optimal truss structure for twenty-one elements truss subjected to second load case is obtained from the product of density which is 7850.2 kg/m^3 with the total volume of the truss structure which give 29.21 kg.

Based on Table 4.14 and Table 4.15, the lowest percentage of accuracy for the displacement of node and elemental stress are 92.2% and 99.8% respectively. The maximum displacement of nodes obtained from the proposed methodology are 7.5 mm downward at both nodes which are N2 and N5, while for SCIA Engineer is 7.2 mm. The maximum elemental stress obtained from the proposed methodology is 226.5 MPa in compression at element B7 while for SCIA Engineer is 226.3 MPa which is just 0.1% different in value.

Since SCIA Engineer able to give output by applying the optimal layout of truss structure generated from the proposed methodology, this shows that the topology obtained from the proposed methodology is feasible. Besides, the accuracy of the results obtained using the proposed methodology are above 90% which can be considered sufficient enough. Thus, the optimal solution obtained from the proposed methodology for twenty-one elements ground structure truss subjected to second load case is validated.

Third load case:

The twenty-one elements ground structure truss subjected to third load case is optimized to generate an optimal truss structure containing ten elements as shown in Figure 4.17. Figure 4.18 shows the model generated from SCIA Engineer with the naming of elements and nodes to provide a clearer presentation of results. The best element cross-sectional areas for twenty-one elements truss subjected to third load case are tabulated in Table 4.16. The nodal displacements and element stresses of the optimal structure obtained from the proposed methodology and SCIA Engineer are tabulated in Table 4.17 and Table 4.18 respectively.

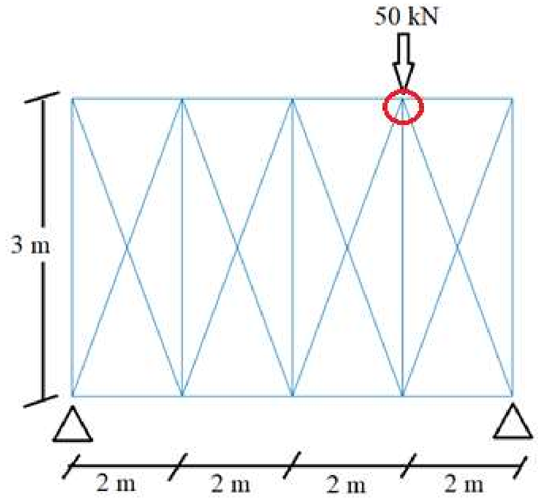

Figure 4.16: Ground Structure of Twenty-One Elements Truss Subjected to Third Load Case

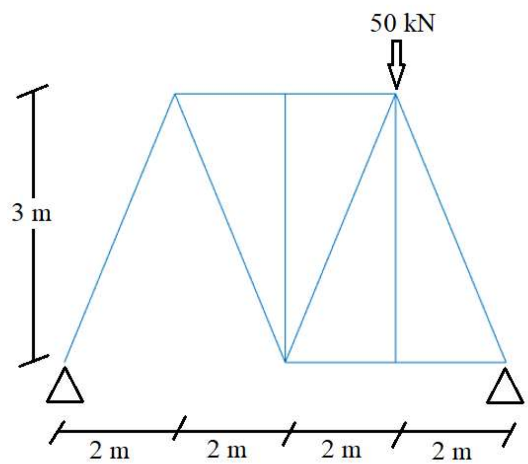

Figure 4.17: Optimal Truss Structure of Twenty-One Elements Truss Subjected to Third Load Case

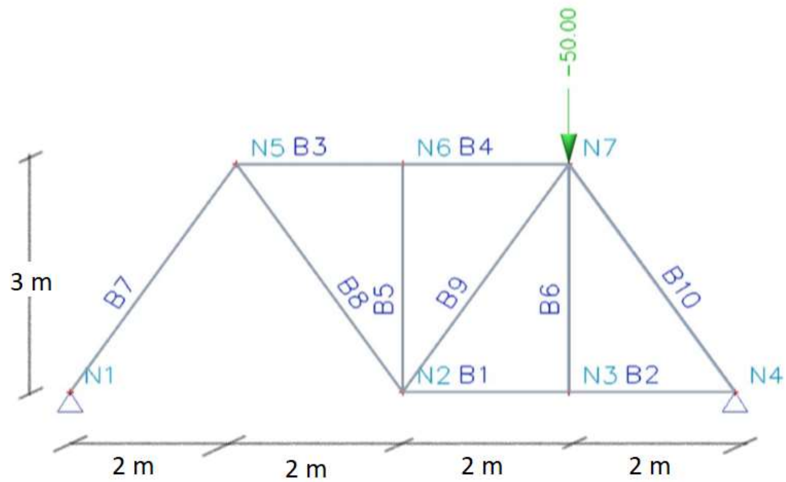

Figure 4.18: Optimal Truss Structure of Twenty-One Elements Truss Subjected to Third Load Case with Naming of Nodes and Elements

Table 4.16: The Best Cross-Sectional Areas of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Third Load Case

Element	Area (mm^2)	Length (mm)	Volume (mm^3)
B1	121.00	2000.00	242000.00
B2	121.00	2000.00	242000.00
B3	121.00	2000.00	242000.00
B4	121.00	2000.00	242000.00
B5	121.00	3000.00	363000.00
B6	121.00	3000.00	363000.00
B7	121.00	3605.55	436271.70
B8	121.00	3605.55	436271.70
B9	121.00	3605.55	436271.70
B10	199.00	3605.55	717504.70
		Total Volume (mm^3)	3720319.82

Table 4.17: Nodal Displacements of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Third Load Case

Displacement of Nodes						
Node	**HS**		**SCIA**		**Accuracy**	
	x (mm)	**y (mm)**	**x (mm)**	**y (mm)**	**x (%)**	**y (%)**
N1	0.0	0.0	0.0	0.0	100.0	100.0
N2	-2.8	-5.6	-2.6	-5.4	94.1	95.7
N3	-1.4	-7.5	-1.3	-7.2	94.1	95.4
N4	0.0	0.0	0.0	0.0	100.0	100.0
N5	-1.2	-1.9	-1.1	-1.8	92.2	94.5
N6	-2.6	-5.6	-2.4	-5.4	93.2	95.7
N7	-3.9	-7.5	-3.7	-7.2	93.5	95.4

Table 4.18: Element Stresses of Optimal Truss Structure for Twenty-One Elements Truss Subjected to Third Load Case

Elemental Stress			
Element	**HS**	**SCIA**	**Accuracy (%)**
	Stress (MPa)	**Stress (MPa)**	
B1	137.7	137.4	99.8
B2	137.7	137.4	99.8
B3	-137.7	-137.4	99.8
B4	-137.7	-137.4	99.8
B5	0.0	0.0	100.0
B6	0.0	0.0	100.0
B7	-124.2	-123.9	99.8
B8	124.2	123.9	99.8
B9	-124.2	-123.9	99.8
B10	-226.5	-226.3	99.9

The best result for optimal truss structure of twenty-one elements truss subjected to third load case reported for the respective nodal coordinates are node N1 (0, 0), node N2 (4, 0), node N3 (6, 0), node N4 (8, 0), node N5 (2, 3), node N6 (4, 3) and node N7 (6, 3) in metre. Based on Table 4.16, the total volume of the optimal truss structure is 3720319.82 mm^3 which is equivalent to 3.72E-3 m^3. The weight of the optimal truss structure for twenty-one elements truss subjected to third load case is obtained from the product of density which is 7850.2 kg/m^3 with the total volume of the truss structure which give 29.21 kg.

Based on Table 4.17 and Table 4.18, the lowest percentage of accuracy for the displacement of node and elemental stress are 92.2% and 99.8% respectively. The maximum displacement of nodes obtained from the proposed methodology are 7.5 mm downward at both nodes which are N3 and N7, while for SCIA Engineer is 7.2 mm. The maximum elemental stress obtained from the proposed methodology is 226.5 MPa in compression at element B10 while for SCIA Engineer is 226.3 MPa which is just 0.1% different in value.

Since SCIA Engineer able to give output by applying the optimal layout of truss structure generated from the proposed methodology, this shows that the topology obtained from the proposed methodology is feasible. Besides, the accuracy of the results obtained using the proposed methodology are above 90% which can be considered sufficient enough. Thus, the optimal solution obtained from the proposed methodology for twenty-one elements ground structure truss subjected to third load case is validated.

4.3 Discrepancy of the Results

The nodal displacements and element stresses obtained using the proposed methodology has minor discrepancies as compared to the output generated by SCIA Engineer. This is because a very small value of 0.001 mm^2 is assigned for the cross-sectional area of those removed elements to avoid any singularity problem in the optimization process.

According to the equation of finite element analysis as shown in Eq. (3.2), the value of the stiffness matrix is affected by the cross-sectional area of the elements by assuming the Young's modulus of steel and length of the elements are constant. When an element is removed in the process of topology optimization, the cross-sectional area of the removed element supposed to has an area of 0.00 mm^2. However, the formation of the stiffness matrix in this study is formed by assigning the removed element with an area of 0.001 mm^2 instead of 0.00 mm^2.

A small changes made in the value of the cross-sectional area will give different value of the stiffness matrix. Thus, it affects the result obtained from the truss analysis. Although a relatively small value of area is assigned to those removed element, the accuracy of the results obtained are more than 90% which indicate that the results obtained using the proposed methodology are still acceptable.

4.4 Simulation Time

The time taken to obtain the optimal solution for eleven, sixteen and twenty-one ground structure trusses using the proposed methodology are recorded and tabulated in Table 4.19, Table 4.20, and Table 4.21 respectively. Figure 4.19 shows the average time taken for the proposed methodology to obtain the optimal solution.

Table 4.19: Simulation Time for Optimization of Eleven Elements Ground Structure Truss

Ground Structure Truss	**Time (s)**
Eleven Elements	37.55
Average Time Taken	37.55

Table 4.20: Simulation Time for Optimization of Sixteen Elements Ground Structure Truss

Ground Structure Truss	**Time (s)**
Sixteen Elements (First Load Case)	473.30
Sixteen Elements (Second Load Case)	450.14
Average Time Taken	461.72

Table 4.21: Simulation Time for Optimization of Twenty-One Elements Ground Structure Truss

Ground Structure Truss	**Time (s)**
Twenty-One Elements (First Load Case)	1653.80
Twenty-One Elements (Second Load Case)	2455.50
Twenty-One Elements (Third Load Case)	2287.40
Average Time Taken	2132.23

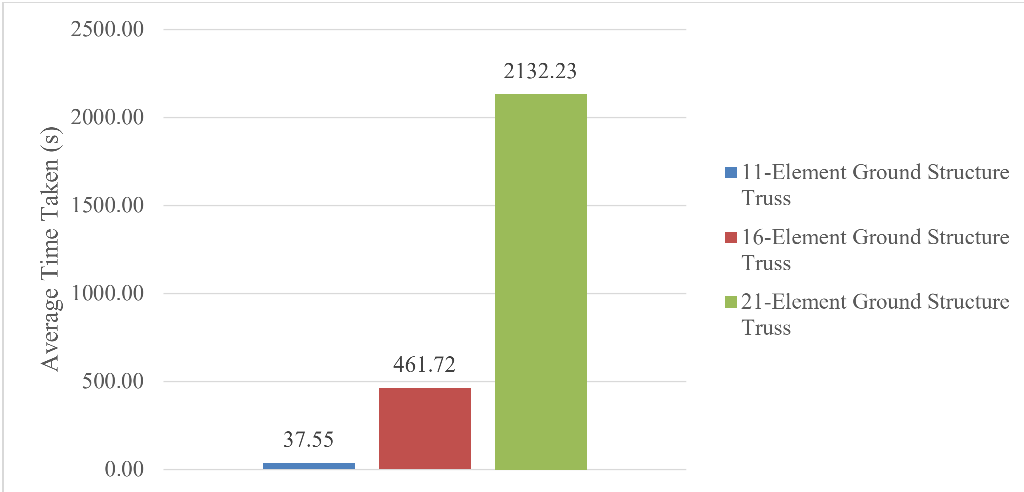

Figure 4.19: Bar Chart of Average Time Taken for Respective Ground Structure to Find a Best Optimum Solution

Based on Figure 4.19, the average time taken for the eleven elements, sixteen elements and twenty-one elements ground structure truss are 37.55 s, 461.72 s and 2132.23 s respectively. The time taken needed to find an optimal sizing and connectivity between the structural member increases when the number of design variable increases. This is because the increase in the number of design variables resulting more calculations needed to perform in the truss analysis which eventually lead into longer time taken to obtain an optimal solution.

Besides, when the number of design variables increase, the chances to generate failed topologies in the process of optimization is higher. The generation of failed topology will cause the optimization process keep looping until a valid topology is obtained. This looping process results in addition of time to seek an optimal solution which lead the time taken become longer.

Thus, increase in the number of design variables will lead the optimization process required more time to obtain an optimal solution due to more calculations is performed and higher chances of failed topology generation.

4.5 Summary

The results obtained using the proposed methodology developed by HS algorithm for eleven elements, sixteen elements and twenty-one elements ground structure truss are validated by comparing the results generated from HS with SCIA Engineer. The percentage accuracy of the results obtained are above 90%.

The difference between the results obtained from the proposed methodology with SCIA Engineer is due to the assignation of a relatively small value of area to those removed element to avoid any singularity problem occur in matrix calculations.

The average simulation time for the optimization of eleven elements, sixteen elements and twenty-one elements ground structure truss are 37.55 s, 461.72 s and 2132.23 s respectively. Increase in the number of design variables will cause the simulation time become longer due to more calculations are needed to perform in truss analysis and the chances to generate failed topologies in the process of optimization is high. As a summary, the optimal results obtained in this study are summarised and tabulated in Table 4.22.

Table 4.22: The Optimal Results Obtained for Eleven Elements, Sixteen Elements and Twenty-One Elements Ground Structure Truss

Ground Structure Truss	Weight (kg)	Time (s)	No. of Optimal Connectivity	No. of Redundant Elements	No. of Redundant Joints
Eleven Elements	18.94	37.55	5	6	2
Sixteen Elements (First Load Case)	26.88	473.30	9	7	2
Sixteen Elements (Second Load Case)	26.64	450.14	9	7	2
Twenty-One Elements (First Load Case)	43.19	1653.80	10	11	3
Twenty-One Elements (Second Load Case)	29.21	2455.50	10	11	3
Twenty-One Elements (Third Load Case)	29.21	2287.40	10	11	3

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 General Conclusion of Research Work

Harmony Search (HS) is a music-inspired algorithm that perform optimization procedures similar to a musician seeking for a best state of harmony for achieving best state of harmony. Easier implementation, strong exploration and exploitation abilities of HS allow this algorithm to perform structural optimization effectively. Thus, HS is proposed as an optimization method to perform truss topology optimization in this study.

A single-stage simultaneous topology and sizing optimization approach is used in this study. Topology optimization problems of trusses with eleven elements, sixteen elements and twenty-one elements with several load conditions subjected to constraints for nodal displacements and element stresses are demonstrated using the proposed methodology. The best results generated from the proposed methodology developed by HS algorithm are compared with the SCIA Engineer software for validation purpose.

Based on the results obtained from the proposed methodology, the best weight for the eleven elements ground structure truss is 18.94 kg. The best weight for the sixteen elements ground structure truss subjected to first load case is 26.88 kg while for second load case is 26.64 kg. For the twenty-one elements ground structure truss, the best weight obtained are 43.19 kg, 29.21 kg and 29.21 kg for the truss structure subjected to first load case, second load case and third load case respectively. The overall accuracy of the results obtained from the proposed methodology for the truss topology optimization problems are 96.25% and 99.82% for displacement of nodes and element stresses respectively.

All the optimal solutions obtained from the proposed methodology are validated to ensure the solutions obtained are feasible and fulfilled all the design requirements with sufficient accuracy. The proposed methodology able to solve truss topology optimization problems by obtaining the optimal joints connectivity between the structural members to produce a truss structure with minimum weight. By using this approach, it is also able to identify redundant truss elements and joints. Thus, the aim and objectives of this study are achieved.

5.2 Recommendations for Future Work

The proposed approach in this study can be extended to investigate on the sizing, shape and topology optimization of truss structures for multiple objectives constrained optimization problems and explore the effectiveness of this approach in various engineering optimization problems.

Besides that, the performance evaluation of proposed approach involves in wider range of problems such as complicated truss frames, perform analysis in three dimensional and real-world complex engineering problems with large number of objectives and constraints would be a possible direction for future work. This future work able to determine its robustness and effectiveness in engineering applications.

The development of solutions to control the number of failed topologies generation is also a possible future study direction. This is because the generation of failed topology does not provide any design solutions and it will constitute complexity in the process of optimization leading the topology optimization process become inefficient. By developing solutions to control failed topologies generation, this provide opportunity for the proposed approach to solve large scale of real-world topology optimization problems efficiently and effectively.

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APPENDICES

APPENDIX A: MELEWAR STEEL TUBE SDN. BHD’s Steel Sections Catalogue

APPENDIX B: SCIA Engineer Structural Analysis Reports