

**A NEW HYBRID OPTIMIZATION METHOD USING DESIGN OF
EXPERIMENT TOGETHER WITH ARTIFICIAL NEURAL GENETIC
ALGORITHM**

By

NOR ZAI AZMIN BIN YAHAYA

**Thesis submitted in fulfilment of the
Requirements for the degree of
Master of Science**

October 2011

ACKNOWLEDGEMENT

IN THE NAME OF ALLAH, THE MOST GRACIOUS AND
THE MOST MERCIFUL

In humbleness, thank you Allah for allowed me to complete this dissertation. I dedicated this work to my beloved parents; Mr. Yahaya bin Mat Rafar and Madam Siti Hawa binti Nordin who always encourage, support and motivate me in many ways.

First of all, I would like to express my deep gratitude and sincere thanks to my supervisor, Dr. Ishak Abdul Azid for his thoughtful supervision, steady support, guidance, critics and comments to improve the dissertation and the content of the research work. Without him, I would not be able to complete my research in such an efficient manner. Apart from them, I would also like to express my appreciation to my fellow colleagues at Universiti Malaysia Perlis, for their moral support and help throughout my research work.

Finally, I express my heartfelt gratitude to my beloved wife and daughters; Noraini binti Othman, Farzana Izzati, Fatinah Irdina, Fadhilah Insyarah and Fatihah Intisar who provided me with love, inspiration, and confidence. Thank you for always being there for making this pursuit worthwhile.

Y. N. Zaiazmin
October 2011

TABLE OF CONTENTS

	Page
ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	ix
LIST OF FIGURES	xi
LIST OF SYMBOLS	xii
LIST OF ABBREVIATIONS	xiv
LIST OF APPENDIXES	xv
ABSTRAK	xvi
ABSTRACT	xvii
CHAPTER 1: INTRODUCTION	Page
1.0 Overview	1
1.1 Engineering design process	1
1.1.1 Engineering design cycle time	3
1.2 Improvement made to reduce engineering design cycle time	4
1.2.1 Engineering design process flow	4
1.2.2 Computer Aided Design (CAD)	6
1.2.3 Computer Aided Engineering (CAE)	6
1.2.4 Computer Aided Manufacturing (CAM)	7
1.2.5 Optimization	7
1.3 Problem statement	8
1.4 Objective and scopes of this study	10
1.5 Significant of the research	11

1.6	Report structure	12
-----	------------------	----

CHAPTER 2: LITERATURE REVIEW Page

2.0	Overview	14
2.1	Current trend in engineering design process	14
2.1.1	Expansion in engineering design process steps/flow	14
2.1.2	Shorter engineering design cycle time	15
2.2	Improvement in the engineering design process	16
2.2.1	Conceptual design	16
2.2.2	CAD/CAM/CAE integration	17
2.2.3	Reverse engineering method	17
2.2.4	Patent verification	18
2.2.5	Knowledge Management	19
2.2.6	Energy efficient and sustainability	19
2.2.7	Concurrent engineering	20
2.2.8	Optimization	21
	2.2.8(a) Classical optimization method	21
	2.2.8(b) Intelligent optimization method	25
2.3	Shortcoming in AI optimization method	27
2.3.1	Determination of the number of the training samples required by ANN	28
2.3.2	Selection on the training method to be used in ANN	29
2.3.3	Determination of the number of neuron and hidden layer used in ANN	30

2.4	Shortcoming of the GA in the Neural Genetic optimization method	30
2.4.1	Constructing constraint function in GA	31
2.5	Existing approached to improve the AI optimization method	31
2.5.1	Improvement on the training samples used to train the ANN	31
2.5.2	Improvement on the training method used to train the ANN	32
2.5.3	Improvement on the number of neurons and hidden Layers used in the ANN	32
2.5.4	Improvement on the number of output neurons for the ANN	33
2.6	Remarks on the literature review	33
2.7	Summary	35

CHAPTER 3: METHODOLOGY	Page	
3.0	Introduction	36
3.1	Optimization process flow	36
3.2	Phase 1 of the hybrid optimization method	38
3.3	Phase 2 of the hybrid optimization method	46
3.4	Phase 3 of the hybrid optimization method	53
3.5	Phase 4 of the hybrid optimization method	59
3.6	Summary	59

CHAPTER 4: IMPLEMENTATION		Page
4.0	Introduction	60
4.1	Case Study	60
4.2	Step 1: Identify all Input Variables and Output Responses	64
4.3	Step 2: Conduct a Screening Experiment	67
4.4	Step 3: Determine the range of input variables	69
4.5	Step 4: Generating a list of experiment	69
4.5.1	Response Surface Central Composite Design Method	70
4.5.2	Taguchi Method	70
4.5.3	D-Optimal Method	70
4.6	Step 5: Conduct the experiment	71
4.6.1	Pre-processing	71
4.6.2	Post-processing	72
4.7	Step 6: Modelling the relationship using Artificial Neural Network	74
4.7.1	Bayesian Regularization training method	76
4.7.2	Levenberg-Marquardt training method	76
4.8	Step 7: Validate the model	77
4.9	Step 8: Find the optimal values using Genetic Algorithm method	78
4.9.1	Constraint parameters	79
4.10	Step 9: Run a confirmation test experiment for validation	81
4.11	Summary	81

CHAPTER 5: RESULTS AND DISCUSSION		Page
5.0	Introduction	82
5.1	Results for step 2: Conduct screening experiment	82
5.2	Results for step 3: Determine the range of all input variables	88
5.3	Results for step 5: Conduct the experiment	88
5.4	Result for step 6: Model the relationship between input variable and output responses	90
5.5	Result for step 7: Validate the model	94
5.5.1	Results for validation test for D-Optimal method	95
5.5.2	ANN model validation test for RSM Central Composite method	96
5.5.3	ANN model validation test for Taguchi method	98
5.5.4	Overall results for validation of the ANN models	100
5.6	Results for step 8: Optimization result by Genetic Algorithm	103
5.7	Results for step 9: Run a confirmation test experiment	104
5.8	Comparison between the classical Response Surface Method results with the ANSYS results	106
5.9	Summary	106
 CHAPTER 6: CONCLUSION		 Page
6.0	Overview	107
6.1	Concluding remarks	107
6.2	Recommendation for future work	108

	Page
REFERENCES	110
APPENDICES	115
LIST OF PUBLICATIONS	119

LIST OF TABLES

	Page	
Table 2.1	Engineering design process steps/flow	15
Table 2.2	Nokia new model phone release date	15
Table 3.1	Manufacturing Process	39
Table 3.2	Design Process	39
Table 3.3	Input variable of two different types	39
Table 3.4	Two Factorial Experiment with resolution III design for four Input Variables	42
Table 3.5	List of experiments for four factors using RSM-CCD method	45
Table 4.1	P-type Silicon Piezoresistive Coefficients	61
Table 4.2	Input Variables for the case study	65
Table 4.3	Output Responses for the case study	66
Table 4.4	Objective Function for the case study	66
Table 4.5	Constraint Function for the case study	67
Table 4.6	Fixed Input Variables for the case study	67
Table 4.7	Two Factorial experiment with resolution III design for four input variables	68
Table 4.8	Input variables for the case study	69
Table 4.9	ANSYS parameters Setting	72
Table 4.10	Input parameters and output responses	75
Table 4.11	Bayesian Regularization training architecture	76
Table 4.12	Levenberg-Marquardt training architecture	77
Table 4.13	Three set of testing the accuracy of ANN prediction	77
Table 4.14	Genetic Algorithm parameter setting	80
Table 5.1	1 st Output response main effect analysis	83

Table 5.2	2 nd Output response main effect analysis	83
Table 5.3	3 rd Output response main effect analysis	84
Table 5.4	4 th Output response main effect analysis	84
Table 5.5	5 th Output response main effect analysis	84
Table 5.6	6 th Output response main effect analysis	85
Table 5.7	Input Variable Range	88
Table 5.8	RSM-CCD experiment runs with output responses	90
Table 5.9	Neurons in input and output layers	91
Table 5.10	ANN prediction results for D-Optimal method for sample no. 1	95
Table 5.11	ANN prediction results for D-Optimal method for sample no. 2	95
Table 5.12	ANN prediction results for D-Optimal method for sample no. 3	96
Table 5.13	ANN prediction results for Central Composite method for sample no. 1	97
Table 5.14	ANN prediction results for Central Composite method for sample no. 2	97
Table 5.15	ANN prediction results for Central Composite method for sample no. 3	98
Table 5.16	ANN prediction results for Taguchi method for sample no. 1	99
Table 5.17	ANN prediction results for Taguchi method for sample no. 2	99
Table 5.18	ANN prediction results for Taguchi method for sample no. 3	100
Table 5.19	Average percentage difference for both ANN training method	101
Table 5.20	The optimum input variables	104
Table 5.21	Output responses based on optimum input variables	104
Table 5.22	Optimum parameters for diaphragm with round boss design	105
Table 5.23	Compare classical RSM method with ANSYS	106

LIST OF FIGURES

	Page	
Figure 1.1	Product life cycle curve	4
Figure 3.1	The nine steps of the hybrid optimization process	37
Figure 3.2	General Artificial Neural Network architecture	48
Figure 3.3	Artificial Neural Network architecture	49
Figure 3.4	Genetic Algorithm flow chart	58
Figure 4.1	Piezoresistive pressure sensor with boss design	60
Figure 4.2	Stress components on the surface of the diaphragm	61
Figure 4.3	Location of piezoresistive material on the diaphragm	63
Figure 4.4	Wheatstone-bridge detection circuit	63
Figure 4.5	Piezoresistive pressure sensor model in ANSYS	72
Figure 4.6	Two nodes selected on top of the pressure sensor diaphragm surface	73
Figure 4.7	Example of nodes extracted from the reference line	74
Figure 4.8	Path created on the top surface of the diaphragm	74
Figure 4.9	Integration of ANN and GA flow chart	79
Figure 5.1	Diaphragm with round boss design results using ANSYS	89
Figure 5.2	Training ANN using Bayesian Regularization method	93
Figure 5.3	Training ANN using Levenberg-Marquardt method	94
Figure 5.4	Overall ANN prediction results for D-Optimal design	96
Figure 5.5	Overall ANN prediction results for Central Composite design	98
Figure 5.6	Overall ANN prediction results for Taguchi design	100
Figure 5.7	Overall performance for both ANN training methods	101

LIST OF SIMBOLS

\bar{x}	Observed value in the experiment result
μ	Mean value of the experiment results
σ	Standard Deviation of the experiment results
n	Number of data or experiment result/observation
a, b, c, d	Coefficient constant for variables
x_1, x_2, x_3, x_4	Input variables
f_1	Neural Network function
$w_{(x1)l}$	Weight for variable x_1
$w_{(x2)l}$	Weight for variable x_2
E_W	Sum of squared network weights
E_D	Sum of squared network errors
α, β	Objective function parameters for regularization parameters
p_i	Input value to a ANN
t_i	Target value to a ANN
$e(i)$	ANN error
$a(i)$	Predicted ANN output value
σ_t	Axial stress
σ_c	Radial stress
π_{ijkl}	Piezoresistive coefficients,

σ_{kl}	Stress applied
$\Delta\rho$	Change in resistivity caused by applied stress
π_l	Longitudinal piezoresistive coefficients
π_t	Transversal piezoresistive coefficients
σ_l	Axis stress
σ_r	Radial stress
ν	Poisson Ratio

LIST OF ABBREVIATION

ANN	Artificial Neural Network
ANOVA	Analysis of Variance
BPNN	Back Propagation Neural Network
BRBPNN	Bayesian Regularization Back Propagation Neural Network
DNA	Deoxyribonucleic Acid
DOE	Design of Experiment
FEA	Finite Element Analysis
GA	Genetic Algorithm
LMBPNN	Levenberg-Marquardt Back Propagation Neural Network
MEMS	Micro Electro Mechanical System
MLR	Multi Layer Regression
MSE	Mean Square Error
NGA	Neural Genetic Algorithm
NN	Neural Network
PSO	Particle Swarm Optimization
RSM	Response Surface Method
RSM-CCD	Response Surface Method with Central Composite Design
SO	Stochastic Optimization
SPM	Surface-mounted Permanent Motor
SSE	Sum of Squared Error

LIST OF APPENDICES

		Page
Appendix A	Results using Response Surface Central Composite Design Method	116
Appendix B	Results using Taguchi Method	117
Appendix C	Results using D-Optimal Method	118

**PENGOPTIMUMAN HIBRID BARU MENGGUNAKAN KAEDAH
REKABENTUK UJIKAJI BERSAMA ALGORITMA NEURAL GENETIK
BUATAN**

ABSTRAK

Di dalam proses rekabentuk kejuruteraan, adalah menjadi satu keperluan untuk mengurangkan masa kitaran rekabentuk kejuruteraan bagi memenuhi permintaan pasaran global dan juga keperluan pelanggan. Di antara langkah-langkah dalam proses rekabentuk kejuruteraan, proses pengoptimumanlah yang banyak menggunakan masa dan sumber. Ini adalah kerana proses pengoptimuman melibatkan banyak parameter dan jumlah penyelesaian tidak terhingga serta perlu menjalankan ujikaji yang banyak. Kaedah pengoptimuman hibrid baru telah dibangunkan melalui penyelidikan ini yang mampu untuk menghasilkan ketepatan ramalan penyelesaian optimum yang lebih tinggi. Pada masa yang sama ianya hanya memerlukan jumlah ujikaji yang minima tanpa menjejaskan ketepatan ramalan. Oleh itu, satu kaedah pengoptimuman hibrid baru telah dibangunkan melibatkan integrasi Rekabentuk Eksperimen (DOE), Rangkaian Neural Buatan (ANN) dan Algoritma Genetik (GA). Hasil daripada kerja penyelidikan ini mendapati bahawa kaedah pengoptimuman hibrid baru telah mengatasi kaedah pengoptimuman klasik secara purata sebanyak 6.3% dari segi meramal penyelesaian yang optimum. Tambahan pula, kaedah pengoptimuman hibrid baru ini juga mengurangkan jumlah bilangan ujikaji yang perlu digunakan untuk melatih ANN. Oleh yang demikian, kaedah baru ini dapat mengurangkan jumlah kos keseluruhan dan memendekkan masa kitaran rekabentuk kejuruteraan.

A NEW HYBRID OPTIMIZATION METHOD USING DESIGN OF EXPERIMENT TOGETHER WITH ARTIFICIAL NEURAL GENETIC ALGORITHM

ABSTRACT

In the engineering design process, it is a necessity to reduce the engineering design cycle time to meet the global market demand and also the customers need. Among the steps in the engineering design process, optimization process always consumed a lot of time and resources. This is because the optimization process involved a lot of parameters and infinite solutions that required a lot of experimental runs. A new a new hybrid optimization has been developed in this research that should be able to yield higher prediction accuracy for the optimal solution and at the same time requires only a minimum number of experimental runs without compromising the prediction accuracy. This new hybrid optimization method is developed by the integration of Design of Experiment (DOE), Artificial Neural Network (ANN) and Genetic Algorithm (GA). As a result of this research work, the new hybrid optimization method has outperformed the classical optimization method in average of 6.3% in terms of predicting the optimal input variables. Furthermore, the new hybrid optimization method reduced the number of experimental runs used to train the ANN, therefore reducing the overall total cost and shorten the engineering design cycle time.

CHAPTER 1

INTRODUCTION

1.0 Overview

In this chapter of the thesis, the introduction to the engineering design process together with the improvement done to reduce the engineering design cycle time will be presented. At the end of this chapter, the problem statement will be highlighted together with the objectives, the scopes and the outlines of this thesis.

1.1 Engineering design process

As mentioned by (Khandani, 2005) “Most of the engineering designs can be classified either as inventions-devices or systems that are created by human effort which are either not exist before or are improvements over existing devices or systems. Inventions, or designs, do not suddenly appear from nowhere. They are the results of bringing together technologies to meet human needs or to solve problems. Design activity occurs over a period of time and requires a step-by-step methodology”.

Engineering design problems are open ended in nature, which means they have more than one right solution. The result or solution to a design problem is a system that possesses specified properties. Solving design problems are often an iterative process. While implementing the solution to a design problem, the discovered solution may be unsafe, too expensive, or will not work. Therefore the design needs to "go back to the drawing board" and the solution needs to be modified until it meets the requirements or specifications.

The engineering design activity is a cyclical or iterative in nature, whereas analytical problem solving is primarily sequential. There are no standard steps in engineering design that are universally accepted by the engineering community. For example, there are 5 engineering design steps as proposed by (Shigley, 1986), 11 engineering design steps as proposed by (Haik & Shahin, 2010), 10 engineering design steps as proposed by (Gomez, Leone, & Gruender, 2004), whereby there are only 10 engineering design steps as proposed by (Hyman, 2002).

In general, the engineering design process has 10 steps (Hyman, 2002). The value of an engineering design process model lies in its ability to help us organize our thoughts and gain insight into important aspects of reality. The 10 steps in the engineering design process as suggested by (Hyman, 2002) are:

- i. Determining the need.
- ii. Defining the problem.
- iii. Determining scopes and limits.
- iv. Choosing theory or model.
- v. Generating alternatives.
- vi. Gathering information.
- vii. Evaluating alternatives.
- viii. Selecting and optimizing.
- ix. Producing or implementing.
- x. Evaluating performance.

1.1.1 Engineering design cycle time

In today's borderless global competition forces company to response quickly to market requirements and needs, which is why the company requires the control of cost, quality, flexibility and time of designing a product (Girard & Doumeingts, 2004). The strong market drive and greater competition forces between companies caused the life cycle of consumer products become shorter over the years. This will caused the company to find ways to reduce the overall time in developing a new product and delivering it to the market as quickly as possible in order to survive in today's borderless economic market.

All products and services have certain life cycles. The life cycle refers to the period from the product's first launch into the market until its final withdrawal from the market (Chung & Wee, 2011). There are four stages in the product life cycle as shown in figure 1.1. The stages are introduction, growth, maturity and decline. Product life cycle will cause a direct effect to the engineering design cycle time. The shorter the product life cycle the shorter the engineering design cycle time will be. For example, nowadays the mobile phone life cycle is around two years before it became obsolete. In order to remain competitive in the mobile phone market, a mobile phone company needs to development a new mobile phone model within one year or half time from the mobile phone life cycle. Failing to do so, the mobile phone company may lose its market share in the mobile phone industry.

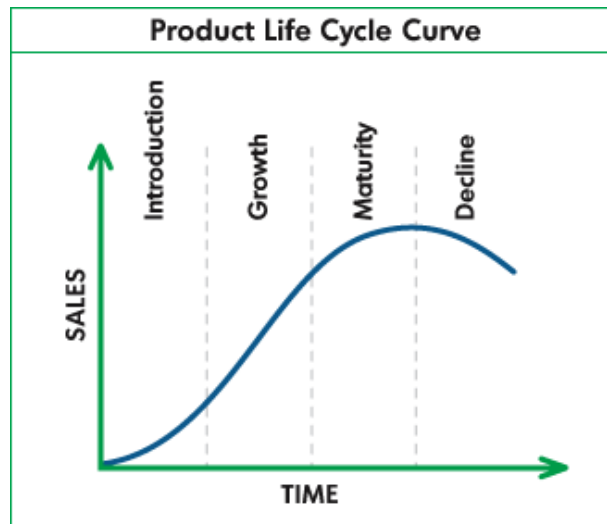


Figure 1.1: Product life cycle curve

1.2 Improvement made to reduce engineering design cycle time

There many improvements made by previous researchers in order to reduce the engineering design cycle time in order to cope with the fast growing market and technology nowadays. The most significant improvements in the engineering design process can be traced back to 1960s where the evolution of the computer technology begins. The computer technology has reduced the engineering design cycle time significantly over the years.

1.2.1 Engineering design process flow

The earliest engineering design process flow can be traced back to 1960s where (Asimow, 1962) has proposed four basic steps in the engineering design process. Below are the four steps proposed by (Asimow, 1962).

- i. Collecting information.
- ii. Design operation.
- iii. Outcome.
- iv. Evaluation.

In 2010 the engineering design process has become more complicated as the knowledge of design grows. The number of engineering design process steps has increased from 4 steps in 1962 to 11 steps in 2010. Below are the 11 steps of engineering design process proposed by (Haik & Shahin, 2010).

- i. Identify customer needs.
- ii. Market analysis.
- iii. Defining goals.
- iv. Establishing functions.
- v. Task specifications.
- vi. Conceptualization.
- vii. Evaluating alternatives.
- viii. Embodiment design.
- ix. Analysis and optimization.
- x. Experiment.
- xi. Marketing.

The improvement in engineering design process steps depends on the company and the product itself. Each company may have different strategy in developing their product thus making the engineering design process different from others. Over the years, the engineering design process become more complicated as more sophisticated product created to fulfill the customer needs. This complicated engineering design process cannot be managed on paper anymore thus required the usage of computer technology and software. Among the pioneers in developing a computer software to manage the engineering design process was introduced by (Edwards, 1994) who created the Designer's Electronic Guidebook to support the

decision making and also to provide the engineering design theories as reference for the designers.

1.2.2 Computer Aided Design (CAD)

In the early years of the engineering design, all the designers used a technical drawing method using paper to design a product. Any changes to the design would lead to redrawing the whole design again on paper. This will consumed a lot of time and resources. In early 1960s, the first Computer Aided Design (CAD) software was created to reduce the engineering design cycle time. The first commercial two-dimensional (2D) CAD software is Design Augmented by Computer (DAC) created by Dr. Patrick J. Hanratty and Fred Krull at General Motors Research Laboratories in USA with collaboration with IBM.

Later on in 1977, the first three-dimensional (3D) CAD software was invented by French aerospace company called Avions Marcel Dassault. They have created a 3D CAD software called Computer Aided Three Dimensional Interactive Application (CATIA) and became the most commercially successful 3D CAD software program in current use. The software has dramatically reduced the engineering design cycle time in drawing the 3D product and multi-angle perspective view for the designed product.

1.2.3 Computer Aided Engineering (CAE)

In engineering design, most of the design required analysis to ensure the safety and the reliability of the design. Before 1960s, all the engineering design analysis is done manually by using hand calculation. Calculating complex

mathematic equations consumed a lot of time. In 1967, Jack Lemon established a Structure Dynamics Research Corporation (SDRC) to help companies to solve engineering design problem using Finite Element Analysis (FEA). The first FEA software was created is called Superb FEA by SDRC (Saxena & Sahay, 2010). By having the Superb FEA software, the engineering design analysis process is becoming faster thus reducing the engineering design cycle time significantly.

1.2.4 Computer Aided Manufacturing (CAM)

Once the engineering design is completed, the next process is to create a prototype. In early years, prototyping is done using wood, clay, boxes and foam. It will take a lot of time and a skillful person to create a prototype. In order to reduce the prototyping time, in 1957 PRONTO was created by Patrick J. Hanratty (Kundra, 1993), the first commercial 3-axis Numerical-Control programming system. By using the PRONTO, the time of making a prototype is reduced significantly. Over the years, the CNC machine is becoming more sophisticated from 3-axis CNC machine in 1957 to 12-axis CNC machine in 2010.

1.2.5 Optimization

Once the design has been analyzed, the next process is to performed optimization process. The optimization process is a method or technology for calculating the best possible solution or combination of variables needed to achieve minimum, maximum or optimal desired result (Gupta, Ballweber, & Allstot, 2001). The desired results can either be minimizing the cost, size, weight, manufacturing time, or improving the durability, safety, or performance.

Generally, there is more than one solution to an engineering design process and usually the first solution is not necessarily the best. In fact, there are a lot of variables, parameters and constraints that need to be considered in the engineering design process. Thus, the need for optimization is very important in the engineering design process in order to find the best solution for the engineering design in the fastest way possible.

Within the steps in the engineering design process, the step that always consumed a lot of time and resources is the optimization process (Ong, Nee, & Xu, 2008). In (Roy, Hinduja, & Teti, 2008) research work, they found that the optimization process in engineering design consumed and needed at least 50 percent of the overall design cycle time. This is because, the optimization process involved a lot of parameters and infinite solutions, and the optimization process is carried out iteratively. Therefore, optimization process needs to carry out as quickly as possible in order to minimize the engineering design cycle time and total design cost.

1.3 Problem statement

In the engineering design process, the need of reducing the engineering design cycle time is directly depends on the duration of the product life cycle. The shorter the product life cycle the less time is required for the engineering design cycle time. Most of the improvements to reduce the engineering design cycle time deal with computer software mainly CAD, CAE and CAM. Over the years, all the software have improved in term of easy to use, faster to design, more accurate analysis and faster to manufacture. Besides the CAD, CAM and CAE, improving the optimization process can also reduce the engineering design cycle time.

According to (Roy, et al., 2008), the optimization process consumed most of the time in the engineering design process. There are a lot of optimization techniques and software in the market that can perform the optimization process. Currently, the optimization process consumed a lot of time by requiring many experimental run and some of the optimization software is unable to find the global optimize solution. In finding the global optimize region, the Artificial Intelligent (AI) optimization method is required. The most common AI optimization method is called Neural Genetic Algorithm (NGA) that consists of integration of Artificial Neural Network (ANN) and Genetic Algorithm (GA).

Optimizing a system using the NGA method has several advantages such as the ANN can model a highly non-linear system or a system that has very complex relationships between input variables and output responses. The ANN requires a lot of experimental data in order for it to model a highly nonlinear model efficiently. The more experimental data provided for ANN training the better the ANN model will be. There is no single proper rule or regulation on how much or how little that the training samples for ANN are needed in order to have a good or workable ANN model that can be used in the optimization process. Too many training samples required a lot of experimental runs that could lead to the increasing of the overall total cost and engineering design cycle time. On the other hand, too little training samples might lead to inaccurate ANN models that could lead to inaccurate predictions of optimal values by the Neural Genetic Algorithm. Besides the ANN, the GA method does not have the ability to narrow the optimization searching method through constraint or limitation parameters. Currently, GA is enabled to solve multiple objective optimization problems using ANN model as the objective

function. Furthermore, there is no proper method on how to integrate ANN model into GA as the limitation or constraint function.

Thus, this research work is an attempt to develop a new hybrid optimization method that can minimize the number of experimental runs or training samples needed to train the ANN without compromising the prediction accuracy of the NGA optimization method. Besides that, a new hybrid optimization method will use one of the ANN model as the constraint function that will be integrated into the GA subroutine to narrowing down the possible solution and to increase the speed of finding the optimal solution. The developed new hybrid optimization method should be able to yield a higher prediction accuracy for the optimal solution and at the same time requires only a minimum number of experimental runs thus reducing the overall engineering design cycle time.

1.4 Objectives and scopes of the study

In this work, there are three objectives that need to be achieved.

1. To identify the best method that minimizes the number of experimental runs used to train the ANN at the same time produce a high degree of accuracy and workable ANN model.
2. To identify the best training algorithm for the ANN that can work well with minimum number of experimental runs and produce a high degree of accuracy and workable ANN model.
3. To integrate an ANN model as the constraint function in the GA subroutine for narrowing down the possible solution and to increase the speed of finding the optimal solution.

The scopes of this research are as follows:-

- i. In identifying the best experiment method to be used that yield a minimum number of experimental runs, only three types of conventional DOE have been studied that is the D-Optimal, Taguchi and Response Surface Method (RSM).
- ii. In determining the best training algorithm for creating the ANN model, only two types of ANN training algorithms have been explored that is the Levenberg-Marquardt back propagation and Bayesian Regularization back propagation.
- iii. In validating the performance of the new hybrid optimization method, a MEMS piezoresistive pressure sensor design will be used as the case study. Only four parameters have been varied in these works that are the diaphragm thickness, diaphragm diameter, boss thickness and boss diameter. SiO₂ is used as the material for the pressure sensor diaphragm and only fixed pressure is to be applied.

1.5 Significance of the research

It is important to develop a new hybrid optimization method that yields higher prediction accuracy for optimal solution with only minimal experiment runs, in order to reduce the engineering design cycle time and total cost for designing an engineering product. From this research work, a fast optimization method will be developed. This method can not only be used in the engineering design stage but also in the optimization of manufacturing processes to improve the machine or process performance and to increase the productivity yield.

1.6 Report Structures

Chapter 1: Introduction

Chapter one will include a brief introduction to the engineering design process and the improvement made to reduce engineering design cycle time. The objectives and scopes of this research are also presented in this chapter.

Chapter 2: Literature review

In chapter two, a literature review regarding improvement made to reduce engineering design cycle time and the previous and current optimization methods together with the shortcoming and improvement of Neural Genetic Optimization methods will be presented.

Chapter 3: Methodology

Chapter three will focus on the detailed steps of the new hybrid optimization process together with the process flow that will be used in this research work.

Chapter 4: Implementation

In chapter four, the implementation of the new hybrid optimization process will be presented. A piezoresistive pressure sensor will be used as the case study for this research work.

Chapter 5: Results and discussion

All the results from the implementation process in chapter four will be presented in details in this chapter. The discussions on the results obtained from the implementation process in chapter four will also be presented.

Chapter 6: Conclusion

Finally in the last chapter, the conclusion of the research work will be presented together with the recommendation for future work.

CHAPTER 2 LITERATURE REVIEW

2.0 Overview

In this chapter, the trend in engineering design process, the improvements in design process and the shortcoming together with the improvements of Artificial Intelligent optimization method will be presented.

2.1 Current trend in engineering design process

In the engineering design process, computer software has becoming the main contribution in making the engineering design cycle time shorter over the years. There are a lot of new computer software are being developed or improved to make the detail engineering design faster and easier. Besides the computer software, the number of engineering design process steps is also increased. This is due to the better understanding of the engineering design process over the years. On the other hand, the product life cycle is becoming shorter over the years due to the market demand and the customer needs for better products.

2.1.1 Expansion in engineering design process steps/flow

The engineering design process steps are increasing over the years starting from 4 steps in 1962 to 11 steps in 2010 and still growing. This is due to the increasing of engineering design process knowledge and rapid development of computer technology and computer software. Besides that, the global demand on sustainability and green technology are also influence the growing numbers of the engineering design process steps. Table 2.1 shows the trend of the number of engineering design process steps from 1962 to 2010.

Table 2.1: Engineering design process steps/flow

No.	Engineering design process	References
1	4 steps	(Asimow, 1962)
2	5 steps	(Shigley, 1986)
3	10 steps	(Hyman, 2002)
4	10 steps	(Gomez, et al., 2004)
5	11 steps	(Haik & Shahin, 2010)

2.1.2 Shorter engineering design cycle time

Nowadays, the trend of the product life cycle is becoming shorter. For example, currently the Nokia mobile phone life cycle is around one year before the product became obsolete (Steinbock, 2010). In order to remain competitive in the mobile phone market, Nokia needs to develop and market a new mobile phone model within six months or half time of the mobile phone life cycle. Failing to do so, Nokia may lose its market share in the mobile phone industry. Table 2.2 shows the Nokia new model phone release date (Steinbock, 2010).

Table 2.2: Nokia new model phone release date

No.	Phone Model	Released Date
1	Nokia C1-00	2010 Q1
2	Nokia C2-00	2010 Q2
3	Nokia C5-00	2010 Q2
4	Nokia C6-00	2010 Q2
5	Nokia C5-03	2010 Q4
6	Nokia C7-00	2010 Q4

2.2 Improvements in the engineering design process

There many improvements made in the engineering design process in order to reduce the engineering design cycle time. This is to cope with the fast growing market and technology. Most of the improvements involve either computer technology or computer software since computer makes engineering design process faster and more efficient. The improvements made in the engineering design process are as follows.

2.2.1 Conceptual design

The conceptual design is the first step in the engineering design process that deal with drawings of a product which include definition or description of the overall concept of the product that need to be designed. In the conceptual design, a designer is required to use his or her creativity to design a product that fulfills the customer requirements and needs. In the conceptual design stage also, the information regarding the manufacturability, reliability, assembability and maintainability also need to be considered. Therefore, in order to process all the information, a lot of time is required to complete the conceptual design process.

In order to reduce the conceptual design time, (Hung, Julian, Chien, & Jin, 2010) has developed a system using enhanced fuzzy weighted average (EGFWA) approach to carry out the analysis and helps the designer to take full advantage of the information available to the designer during the conceptual design stage. By having the EGFWA system, the decision making process in developing a conceptual design become more effective (Hung, et al., 2010).

2.2.2 CAD/CAM/CAE integration

The number of Computer Aided Design, Computer Aided Manufacturing and Computer Aided Engineering (CAD/CAM/CAE) application and their capability has risen greatly in recent times. These software are becoming more sophisticated over the years and require a lot of computational power and memory to run them. A high computational power and memory computer is very expensive. A design company may require several high end computers to design, analysis and to simulate a product in computer. This could lead to increasing of overall total cost in developing a product.

In order to reduce the overall total cost in developing a product, (Bettig & Bapat, 2006) in their research is trying to integrate multiple information in a single CAD/CAM/CAE environment to reduce the required large computer memory and high computational power. This could lead to having a medium price computer that able to run CAD/CAM/CAE software. By able to reduce the high consumption of computer memory and computational power, the CAD/CAM/CAE software can fun faster and more efficient. Thus lead to saving overall time and cost in designing a product.

2.2.3 Reverse engineering method

Reverse engineering is taking apart or analyzing an object to see how it works in order to duplicate or enhance the object. Reverse engineering can be used to design a product by scanning the product or digitizing the original product shape and transferred the data or information collected to CAD software. The digitizing

process consumed a lot of time especially if the product is so complicated. This is because the digitizing process needs to be done for all orientations of the object.

In order to reduce the digitizing time in the reverse engineering process, (Germani, Mandorli, Mengoni, & Raffaelli, 2010) in their research has study a new method of laser scanning technology (non-contact method) that could reduce the digitizing time up to 45 percent compared to contact method of digitizing. They also claimed that the new method improve the accuracy of the digitizing image compared to the traditional contact method of reverse engineering. This new digitizing method could lead to better product quality and at the same time reduced the time in designing a new product.

2.2.4 Patent verification

A patent is a set of exclusive rights granted by government of a country to an inventor to protect his or her 'Intellectual Property' for a limited period of time before disclosure the invention to the public. In the engineering design, there will be a case where the designed product is similar to a product that has been patented before by other designer. By manufacturing a similar product that has been patented before may lead to legal action issued by the patent holder.

In order to avoid any legal action issued by a patent holder once the product has been released to the market, (OuYang & Weng, 2011) has proposed a new comprehensive patent analysis model (NCPA) incorporated into the detail design stage in the engineering design process. This is to ensure that the design will not resemble any patented product in the market. (OuYang & Weng, 2011) claimed that

the NCPA system improves the overall efficiency of a new product design but also involved higher cost than other approaches dealing with patent verification process.

2.2.5 Knowledge Management

Knowledge Management (KM) is the discipline of enabling individuals, teams and entire organizations to collectively and systematically create, share and apply knowledge, to better achieve their objectives (Nonaka & Takeuchi, 1995). In engineering design process, almost all designers experience the same design process over and over throughout his or her career. But the process of designing is embedded inside the head of the designer. The design knowledge can somehow disappear or lost if the designer retired or joining a different design company.

To avoid the knowledge of senior designer being lost (Roldán, Gonnet, & Leone, 2010) has developed a computer software called TracED. The TracED software retained all the designer knowledge regarding the design process, selection of material, safety standard, environmental issue, manufacturability and mechanical and electrical component selection. Learning from the mistakes done in previous design and the trick or shortcut in designing the complex part could improved the quality of the design thus definitely reduces the engineering design cycle time.

2.2.6 Energy efficient and sustainability

Global demands are growing substantially to achieve energy efficient and sustainable resources to reduce the consumption of world's resources and to provide better future for our children. In engineering design process, there is a need to make physical prototype in order to test the product. In many cases, there is a need to

produce several prototypes due to major or minor adjustment or improvement on the design. Once the analysis on the prototypes is completed, the unwanted prototypes are thrown away and become a waste. Making prototype itself consumed a lot of materials, electrical energy, resources and manpower.

In order to reduce on making a lot of prototypes, (Stark et al., 2010) has developed a Virtual Product Creation technique that could reduced the number of physical prototype by introducing Virtual Reality 3D of the product. This will reduce the usage of material on building prototypes, reduce energy of making the prototypes and reduce the pollution caused by unwanted prototypes. By having this Virtual Reality 3D technology, the usage of raw material can be minimized thus lead to less pollution and energy efficient.

2.2.7 Concurrent engineering

As mentioned by (Anderson, 2004). “Concurrent engineering is a method by which several teams within an organization work simultaneously to develop new products and services. By engaging in multiple aspects of development concurrently, the amount of time involved in getting a new product to the market is decreased significantly.” In the engineering design process, almost all complex designs required multidiscipline design groups focus on designing specialize items. In order to complete the design in the fastest way possible, all the designer need to work concurrently with efficient communication between the designers, project managers and also suppliers. Currently, there is no computer software to manage the concurrent engineering process. This could lead to miss communication among

designers, managers and suppliers. Miss communication can lead to mistakes and waste a lot of time and resources.

In order to manage the concurrent engineering process, (Heer & Würzberger, 2011) has come out with a software called PROCEED (Process Management Environment for Engineering Design processes). This software is used as a communication platform for all designers, managers and suppliers. This software is also cooperated with project monitoring system to coordinate the engineering design process among designers.

2.2.8 Optimization

There are many types of optimization method currently being used in various engineering and research fields. Each optimization method has its own strengths and weaknesses. The main objective of all optimization method is to find the optimal solutions, values or parameters. In the engineering design process, there are two categories of optimization methods that are usually being used. The two categories are classical optimization method and intelligent optimization method. A brief explanation regarding the two optimization methods are as following.

2.2.8(a) Classical optimization method

The classical optimization method is also known as statistical Design of Experiment (DOE) method is a structured and organized method utilizing statistical technique for determining the minimum or maximum value for a function or a model. Design of Experiment (DOE) is a method which involves designing a set of experiments in which all relevant factors are varied systematically (Gupta, et al.,

2001). It is widely used by researchers in almost all fields as the first step in solving the optimization problems. In the DOE there are several established classical optimization methods that are widely used in the research field such as Full Factorial method, Partial Factorial method, Taguchi method and Response Surface method.

i) Factorial method

Factorial designs were first used in the 19th century by John Bennet Lawes and Joseph Henry Gilbert of the Rothamsted Experimental Station (Yates, 1970). Information gathered from factorial experiments can be analyzed using Analysis of Variance (ANOVA) or regression analysis techniques in order to determine the dominant input variable that gives the biggest effect to the output response. In factorial design method also there are several useful exploratory analysis tools such as the main effects plots, interaction plots, and a normal probability plot of the estimated effects that can be used to analyze the data and to understand the system better. Besides that, full factorial or fractional factorial methods are considered as an easy way to estimate a first-degree polynomial model a using linear regression technique.

However, the limitation of the Factorial method is that it needs a lot of experimental runs in order to suggest the optimal value. In other words, Factorial method it is an iterative optimization method. Most of the time where time and cost of running an experiment are the major constraint, the researcher were unable to conduct a lot of experimental runs. This will cause the Factorial method were unable to efficiently process the experimental data using ANOVA. Therefore, in

order to reduce the number of experimental runs at the same time able to optimize the process, Taguchi method is proposed by Genichi Taguchi.

ii) Taguchi method

Taguchi method is a statistical method developed by Genichi Taguchi in 1970s initially to improve the quality of manufactured goods. Orthogonal arrays are frequently used in a technique promoted by Taguchi (Phadke, 1989). (Tai-Yu, 1996) confirmed that by applying the Taguchi method and the use of orthogonal array, the number of experiment runs is reduced significantly thus reducing the total time and cost of his research.

However, the limitation of the Taguchi method is that it can only model a linear relationship between input variables and output responses with slope detection. Since most of the engineering problems involved many variables that could lead to a nonlinear relationship between input variables and output responses. The Taguchi method is therefore not suitable for optimizing a nonlinear system. Therefore a new optimization method that has the ability to model nonlinear relationship between input variables and output responses is developed. The optimization method is called Response Surface method (RSM) founded by Wishart, Wanson, and Mitschalich.

iii) Response Surface Method (RSM)

Response Surface method (RSM) can be traced back to the works of Wishart, Wanson, and Mitschalich in the early 1930s and it was not until 1951, that RSM was formally developed by G. E. P. Box and K. B. Wilson. Their original

objective was to explore the relationships between the yield of a chemical process and a set of input variables presumed to influence the yield. Due to the pioneering work done by Box and his co-workers, RSM has been successfully used and applied in many different areas such as chemical engineering, industrial development and process improvement, agricultural and biological research (Chih-Chou, Pignatiello, & Cook, 1994).

The main idea of RSM is to run well structured experiments that covered evenly in design space (input variables range). Once all the experiments have been conducted, using the experimental data a model is formulated either using linear, quadratic or cubic model structure using a regression analysis method. Then, numerical analysis method is used to find the optimal value based on the formulated model.

However, the limitation of the Response Surface Method is that the numerical analysis method either using steepest descent or steepest ascent method used as the optimization search engine has a strong tendency to stuck or converge at the local optimal point rather than at the global optimal point. This will cause inaccurate prediction of the optimal value. Furthermore, RSM only works best if the model is linear, quadratic or cubic without noise (deterministic model) and it cannot work efficiently if the model is highly nonlinear and polluted with noise (stochastic model). Due to this limitation, an Artificial Intelligent (AI) optimization method is developed.