DEVELOPMENT OF MULTI CRITERIA DECISION MAKING MODEL FOR SUPPLIER SELECTION USING GENE EXPRESSION PROGRAMMING

ALIREZA FALLAHPOUR

**FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR**

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ALIREZA FALLAHPOUR

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ABSTRACT

Sustainable Supply Chain Management (SSCM) is a developing concept recently applied by organizations, due to the growth in awareness about sustainability in firms. The literature reports that a significant way to implement responsible SSCM is to ensure that the supplier of goods successfully incorporates sustainable attributes. However, it is seen that the previous studies in this field did not adequately discern the sustainability criteria and sub-criteria and put the sustainable issues in a form of generic model. Generally, in supplier selection process, two issues are very important: 1) selecting correct evaluative criteria which are important and applicable in the real world; 2) using accurate model for performance evaluation and ranking.This study takes the aforementioned issues into account, develops a comprehensive list of criteria and their corresponding sub-criteria and also, a new intelligent approach known as Gene Expression Programming (GEP) is used to overcome the shortcoming of the previous proposed intelligent models in the field of supplier selection. A comprehensive list of criteria and sub-criteria was developed. Investigation of the developed criteria and sub-criteria in terms of their importance and applicability was carried out through a questionnaire survey, using experts' opinions from the different industry and the academia. To show the validity of the collected data set by the questionnaire, Cronbach's alpha and Mann-Whitney U-test were carried out. Following this, GEP was performed to overcome any drawback developed by previously proposed models (called black box). To verify the validity of the GEP model, different statistical methods were applied. In addition, the derived results were compared with both previous intelligent model such as Adaptive Neuro Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) to show the accuracy of the proposed model in performance evaluation. Furthermore, to demonstrate GEP's great capability in ranking, the ranking result of the model was compared to the result obtained by one of the most common

methods in ranking, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

ABSTRAK

Pengurusan Rantaian Bekalan Lestari (SSCM) merupakan konsep yang pesat membangunkan sedang digunapakai oleh organisasi, disebabkan oleh munculnya kesedaran mengenai keperluan kemampanan dalam sesebuah firma. Kajian melaporkan antara cara yang signifikan dalam melaksanakan tanggungjawab SSCM adalah dengan memastikan golongan pembekal berjaya menggabungkan sifat-sifat yang mampan. Walaubagaimanapun, kajian yang terhasil sebelum ini didapati tidak memadai untuk membezakan antara kriteria dan sub-kriteria kemampanan yang membolehkan isu-isu kemampatan membentuk satu model generik. Secara umumnya, dalam proses pemilihan pembekal, terdapat dua isu yang sangat penting: 1) memilih kriteria menilai yang penting dan dapat diguna pakai dalam dunia sebenar secara tepat; 2) menggunakan model yang tepat untuk penilaian prestasi dan ranking. Dengan mengambil kira isu-isu yang dinyatakan di atas, kajian ini bertujuan membangunkan senarai komprehensif kriteria dan sub-kriteria yang berkaitan disamping menggunakan pendekatan pintar baru yang dikenali sebagai Pengaturcaraan Ekspresi Gen (GEP) untuk mengatasi kepincangan model pintar sedia ada dalam bidang pemilihan pembekal. Senarai komprehensif kriteria dan sub-kriteria telah dibangunkan. Kaji selidik dari segi kepentingan dan kesesuaian keatas kriteria dan sub-kriteria telah dijalankan dengan mendapatkan pandangan pakar daripada industri yang berbeza dan juga dari kalangan akademik. Bagi memastikan kesahihan data yang diperolehi melalui kaji selidik tersebut, ujian kebolehpercayaan Cronbach's alpha dan Mann-Whitney U telah dijalankan. Berikutan itu, GEP dilaksanakan untuk mengatasi sebarang kelemahan yang terhasil dari model yang dicadangkan sebelum ini (yang dikenali sebagai kotak hitam). Untuk mengesahkan kesahihan model GEP, beberapa kaedah statistik telah digunakan. Di samping itu, bagi memastikan ketepatan model yang dicadangkan dalam penilaian prestasi, keputusan yang diperolehi dibandingkan dengan kedua-dua model pintar yang

telah dibangunkan sebelum ini seperti Adaptive Neuro Fuzzy Inference System (ANFIS) dan Artificial Neural Network (ANN). Selain dari itu, untuk menunjukkan kehebatan GEP dalam ranking, keputusan ranking yang diperoleh dari GEP dibandingkan dengan keputusan yang diperolehi dari salah satu kaedah yang paling kerap digunakan dalam melakukan ranking iaitu Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

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With best wishes to all of them,

Alireza Fallahpour

Author

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LIST OF SYMBOLS AND ABBREVIATIONS

AHP	Analytical Hierarchy Process
AI	Artificial Intelligent
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ANP	Analytic Network Process
AR	Annual Revenue
BCC	Bruja, Cooper, Rhodes
BP	Back Propagation
MSE	Mean Squared Error
C	Cost
CBR	Case Based Reasoning
CCR	Charnes, Cooper, Rhodes
COA	Center of Area
DEA	Data Envelopment Analysis
DEMATEL	Decision Making Trial and Evaluation Laboratory
DMU	Decision Making Unit
DOA	Discount On Amount
DOC	Discount On Cash
DS	Delivery & Service
DT	Decision Tree
Eco.D	Eco-Design
Env.M.S	Environmental Management System
F	Flexibility
FAHP	Fuzzy Analytical Hierarchy Process

FANP	Fuzzy Analytical Network Process
FIS	Fuzzy Inference System
G.P	Green Product
G.Te	Green Technology
G.Tr	Green Transportation
G.W	Green Warehousing
GA	Genetic Algorithm
GEP	Gene Expression Programming
GP	Goal Programming
HSW	Health and Safety at Work
LP	Linear Programming
LS-SVM	Least Square-Support Vector Machine
MADM	Multi-Attribute Decision Making
MCDM	Multi-Criteria Decision Making
MILP	Mixed Integer Linear Programming
MLP	Multi Layere Perceptron
MOP	Multi Objective Programming
MP	Mathematical Programming
MQ	Material Quality
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
PT	Payment Term
Q	Quality
SA	Supportive Activities
SCM	Supply Chain Management
SSCM	Sustainable Supply Chain Management

SVM	Support Vector Machine
TOPSIS	Technique for Order Performance by Similarity to Ideal Solution
VIKOR	Vlsekriterijumska Optimizacija I Kompromisno Resenje
WR	Workers ‘Rights

CHAPTER 1: INTRODUCTION

1.1 Introduction

This part includes the background of the issues that are pertinent to the topic of research. Supplier evaluation and selection is a very critical issue in the success of Supply Chain Management (SCM) of organizations. This thesis proposes a predictive intelligent decision making model for evaluating and selecting the most suitable suppliers and provides a list of sustainable criteria and their corresponding sub-criteria as well as measure their importance and applicability.

In the following, the sub-sections related to background of research, problem statement, research aims and objectives, scope of the research, contribution of the research and organization of the research are presented.

1.2 Background of research

Currently, SCM has become one of the most significant concerns in any manufacturing company in terms of obtaining successful outcomes. SCM is an emerging field that has commanded attention and support from the industrial community (Liang et al., 2006). SCM consists of all the activities related to the transformation and flow of goods and services, including their attendant information flows, from the sources of the materials to the end users (Büyüközkan et al., 2011) that lead to improved competitive advantage, reduced supply chain risk, reduced production risk, increased revenue, improved customer service, optimized inventory level, and increased customer satisfaction and profitability (Boran et al., 2009; Chang et al., 2011).

In the past decade, environmental and social concerns have attracted significant attention in the name of sustainable development. Due to the increasing awareness of environmental protection, increasing attention on behalf of training managers in sustainable management and the development of theory to support sustainable managerial decision making, sustainability has become very important to organizations (Govindan et al., 2013a). Therefore, managers try to implement new rules and strict standards to strengthen their own the competitive position in the market. As an extremely important business issue, Sustainable SCM (SSCM) can be regarded as a concept that includes the management of material, information and capital flows, as well as cooperation between companies along the supply chain while taking into account the goals from all three dimensions, economic, environmental and social – of sustainable development derived from customer and stakeholder requirements (Amindoust et al., 2012; Büyüközkan et al., 2011).

Sarkis et al., (2014) stated that one of the critical issues in SSCM is that of supplier selection. Consideration of the environmental, social and economic performance of the suppliers is necessary for effective sustainable supplier evaluation and selection. However, in the process, the determination of sustainable practices (as the criteria) has been a problem in which a multi-criteria decision making (MCDM) tool can be a useful aid (Rostamzadeh et al., 2015). In addition, it could be said that the issues relating to sustainable supplier selection have been given little attention in the literature (Amindoust et al., 2012).

In general, it has been reported that in the field of supplier selection due to presence of conflicting criteria such as quality, cost, etc., evaluating and selecting appropriate suppliers is a complicated process (Bhattacharya et al., 2010; Humphreys et al., 2003). Therefore, the issue of supplier evaluation and selection has received much attention from academics and practitioners. Consequently, various solo and hybrid methods have been proposed for supplier evaluation and selection.

Individual techniques such as non-parametric approach (Data Envelopment Analysis (DEA)), Multi Attribute Decision Making (Analytical Hierarchy Process (AHP) (Deng et al., 2014; Peng, 2012; Rajesh et al., 2013), Analytic Network Process (ANP) (Dargi et al., 2014; Demirtas et al., 2008; Theißen et al., 2014), Elimination and Choice Expressing Reality (ELECTRE) (Chen, 2014; Montazer et al., 2009; Teixeira De Almeida, 2007),, parametric approaches (Regression), Artificial Intelligent (AI) approaches (optimization such as Genetci Algorithm (GA), Particlre Sworm Optimization (PSO) and prediction such as Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS), Fuzzy Inference System (FIS), etc.) and integrated techniques like DEA-ANN (D. Wu, 2009), MCDM-ANN (Lakshmanpriya et al., 2013), MCDM-DEA (Ramanathan, 2007) have been developed.

In the recent decade, the literature reports that the predictive AI approaches have become very attractive models in supplier evaluation and selection. However, to the best of our best knowledge, research on sustainable supplier selection using AI-based techniques is rare.

Based on the literature, it can be said that there are two main predictive AI-based techniques for supplier selection: i) pure AI-based models such as ANFIS(Güneri et al., 2011), FIS-based (Amindoust et al., 2012), SVM (Vahdani et al., 2012) ; ii) integrated AI-based models such as DEA-ANN (Wu et al., 2006), DEA-SVM (Jiang et al., 2013), MCDM-ANN (Golmohammadi, 2011), MCDM-GA-ANN (Golmohammadi et al., 2009).

Baykasoğlu et al.,(2009) stated that GEP is the best intelligent-based technique for simulating the due date assignment in comparison with the existing models. Gandomi et al., (2011) indicated that although the existing AI-based models are very useful, their common drawback is that they are considered black box tools. That is, they are unable to provide an explicit mathematical model of supplier performance based on criteria (as the inputs) and only provide an AI (neural based, ANFIS-based or FIS-based) structure for predicting supplier performance. The following issues are the main problems of the previous predictive intelligent approach in supplier selection:

I. There is no point of an intangible structure which only estimates the performance without any equation

II. These structures cannot facilitate the supplier evaluation process for managers if the existing AI technique is in strong need of special knowledge

III. The managers are unable to analyze the behavior of the suppliers when they do not know what kind of mathematical relationship exists between the performance and determined criteria

In addition to the models, the issue of choosing the right evaluative criteria and their corresponding sub-criteria is one of the critical concerns in the field of supplier selection. Various criteria and sub-criteria have been applied for assessment. However, there is a lack of developing a list of criteria and sub-criteria and measuring their importance and applicability in the real world.

This research study focuses on development of intelligent decision model (to solve the black box problem) using a new and robust pure predictive AI-based technique known as Gene Expression Programming (GEP) which overcomes the problem related to the black box for supplier evaluation and selection as well as provides a comprehensive list of the most important and applicable criteria and sub-criteria for performance evaluation of the sustainability of suppliers.

1.3 Problem Statement

SCM is a very important issue in increasing the efficiency of organizations. At present, sustainability has become a very significant matter because of government regulations, public awareness of climate change, etc. Consequently, managers of firms focus on linking sustainability with SCM. The literature reports that one of the basic methods to improve the performance of SCM in sustainability is to select the best suppliers with respect to sustainability attributes.

Generally, in the process of supplier performance evaluation and selection, using appropriate evaluative criteria and an accurate and applicable model are very effective. The literature reports that the issue of sustainable supplier selection has recently received serious attention. However, a comprehensive set of criteria and their corresponding sub-criteria for aiding managers in assessing suppliers' performance is found lacking. Moreover, it can be said that in the recent decade, applying intelligent based techniques have been given much attention in the area of supplier selection. Although it has been proved that their accuracy is high in performance estimation, there are some problems they cannot cover (mentioned in section 1.2).

It has been seen in literature that the previous studies are very generic and theory based without consideration of their usefulness to decision makers and application to the real world. Therefore, there is a need to propose a robust and practical decision making model for selecting optimal sustainable supplier in manufacturing based on a comprehensive set of criteria and sub-criteria.

1.4 Research Aims and Objectives

This section presents the research aims and objectives of this research study.

1.4.1 Research Aim

This research aims at developing intelligent decision model for suppliers' performance evaluation and selection in manufacturing industries as well as providing a comprehensive list of important and applicable criteria for sustainable supplier selection. This study proposes a model to facilitate the decision making process and helps managers of manufacturing companies in decision making.

1.4.2 Research Objectives (RO) and Research Questions (RQ)

The research objectives for the study are:

RO1: To develop a list of important and applicable criteria for the evaluation of a supplier's sustainability performance in the manufacturing industry.

RQ1: which list of criteria is suitable to evaluate the suppliers' sustainability performance of manufacturing industry?

RO2: To develop an open-ended GEP-based model for sustainable supplier selection.

RQ2: How to assess the sustainability performance of the suppliers?

RO3: To investigate the performance of the proposed model using the different methods.

RQ3: How to evaluate the accuracy of the developed model?

1.5 Scope of research study

Due to increasing public awareness of climate change, higher clarity related to the environmental and social actions of organizations, firms have started to undertake major initiatives to transform their supply chain processes. These sustainability matters and supply chain operations with consideration of sustainability have received much attention in recent decades. Sustainability issues and industrial growth are thus combined together with SCM in terms of their contribution to SSCM. As sustainable suppliers affect directly the SSCM performance, thus firms must focus on sustainable suppliers. Therefore, it is worthy to conduct a research which is more focused than generic. Manufacturing industries is where that strongly need to focuse on sustainable supplier selection.

Although many studies have been done in this area, but it is seen that there is a need to determine a comprehensive a list of criteria and their corresponding sub-criteria and measure their importance and applicability. Also, it can be observed that in the recent decade among the existing models, the predictive intelligent-based models have been increasingly used for suolving the problem of performance evaluation and selection. Although these models are very robust and accurate, but the existing AI-based models are considered as black box which means they cannot provide the decision makers an explicit mathematical model for suppliers' performance based on the criteria. So, there is a need to introduce a new intelligent model for solving the black box problem in the field of sustainable supplier selection.

The scope of this study is to develop predictive intelligent-based decision making model for supplier selection based on the important and applicable sustainability criteria for manufacturing industry. In fact, by developing the list of the criteria and sub-criteria, the managers of the manufacturing industries can understand how to evaluate the suppliers' sustainability performance. Furthermore, by measuring their importance and applicability, the managers can understand which criteria are the most effective attributes on the suppliers' sustainability performance. In addition, by implementing the GEP-based model the decision makers can analyze the behavior of the suppliers and estimate their performance that means, the managers not only can estimate the suppliers performance and determine the weak suppliers but also they can improve the weak suppliers' performance by using the model.

1.6 Contribution of the research

The current study proposes an intelligent model for supplier performance evaluation and selection with respect to sustainability criteria for industries, which is applicable for any size of enterprise.

One of the main contributions of this study is to develop a comprehensive list of criteria and sub-criteria as well as measuring their importance and applicability for using a questionnaire-based survey for the assessment of suppliers' performance in manufacturing industry. This can be found in Chapter 4.

This study also contributes to the use of GEP approach in the area of supplier selection. As stated before, the existing AI- models in the area of SCM are considered as black box. It means, they cannot generate a mathematical model for the performance based on the determined attributes. In this research, the mathematical model based on the performance history of the suppliers is developed using the GEP approach.

1.7 Organization of the research

The rest of the thesis is as follows: The related literature review is presented in the second chapter. In chapter three, the methodology of research, error measurement factors, evaluation methods for verifying the robustness of the model and the source of the theoretical information are given. In chapter four, the first objective of the research is achieved by developing a list of criteria and sub-criteria for evaluating the sustainability of suppliers' performance. Also, the importance and applicability of the determined criteria and sub-criteria are established In this chapter the first objective is achieved. In chapter five, the aims and assumptions of the proposed GEP model are described as well as the drawbacks of the previous AI models. In chapter six, the real case study is shown and the results related to the implementation of the GEP model are presented. In chapters five and six the second objective is achieved. Chapter seven shows the validity of the proposed model using different methods. In this chapter, the third objective is achieved. The last chapter summarizes the research, presents the conclusions and future works and the limitations.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This section consists of two sub-sections. The first sub-section presents a brief overview of the decision making techniques in supplier selection. Then, in the second sub-section, the most important sustainability criteria are presented.

In response to government legislation, public awareness of climate change, higher clarity related to the environmental and social actions of organizations, firms have started to undertake major initiatives to transform their supply chain processes. These sustainability matters and supply chain operations with consideration of sustainability have received much attention in recent decades. Sustainability issues and industrial growth are thus combined together with SCM in terms of their contribution to SSCM. As stated earlier, supplier selection is a process that is very effective in the improvement of SCM. Therefore, to increase the efficiency of SSCM, firms must focus on sustainable suppliers and have long term model to evaluate their suppliers based on the sustainability criteria.

In general, in order to choose the proper suppliers, two subjects including the selection of suitable criteria and the use of efficient techniques for evaluation of supplier performance with respect to these criteria are essential (Amindoust et al., 2012).

2.2 Decision making techniques for supplier selection

Many qualitative and quantitative approaches have been proposed for selecting the optimal supplier. Based on the literature, the techniques proposed in this area can be divided into individual and integrated approaches.

2.2.1 The individual models

These models are categorized into three parts which is discussed below.

2.2.1.1 Multi-Attributes Decision Making (MADM)/MCDM methods

These methods include Analytic Hierarchy Process (AHP) (Deng et al., 2014; Peng, 2012; Rajesh et al., 2013), Analytic Network Process (ANP) (Dargi et al., 2014; Demirtas et al., 2008; Theißen et al., 2014), Elimination and Choice Expressing Reality (ELECTRE) (Chen, 2014; Montazer et al., 2009; Almeida, 2007), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (Dulmin et al., 2003; Yilmaz et al., 2011), Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) (Kannan et al., 2014; Liao et al., 2011; Junior et al., 2014) , Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Liu et al., 2014; Sanayei et al., 2010; Shemshadi et al., 2011), Decision Making Trial and Evaluation Laboratory (DEMATEL) (Chang et al., 2011; Ho et al., 2012; Hsu et al., 2013).

Boran et al., (2009) proposed an intuitionistic fuzzy TOPSIS to rank suppliers and select the best one. The model comprises 8 steps: 1) calculating the weights of decision makers, 2) making aggregated intuitionistic fuzzy decision matrix based on the experts' idea, 3) evaluating the weight of each criterion, 4) making aggregated weighted intuitionistic fuzzy decision matrix, 5) gaining intuitionistic fuzzy positive-ideal solution and intuitionistic fuzzy negative-ideal solution, 6) computing the separation measures, 7) determining the relative closeness coefficient to the intuitionistic ideal solution, 8) ranking the alternatives. The model was implemented in an automotive company. Quality, Cost, Delivery and Relationship closeness were determined as the evaluative criteria for assessing five suppliers. The results concluded that intuitionistic fuzzy sets are an appropriate technique to deal with uncertainty.

Sanayei et al., (2010) extended VIKOR method under fuzzy environment. There are three main steps in that model including: 1) determining important criteria, 2) measuring the importance of each attribute using trapezoidal fuzzy number, 3) evaluating suppliers and selecting the most suitable suppliers using VIKOR method. In their case study, five suppliers were evaluated based on Quality, Cost, Delivery, Level of technology and Flexibility. Each attribute was assessed based on three decision makers' opinions under trapezoidal fuzzy number. After collecting the fuzzy data set, the crisp values are gathered using Center of Area (COA). Finally, the most suitable supplier is determined using VIKOR.

Chang et al., (2011) proposed an integrated model. First, they combined fuzzy set theory with DEMATAL to find effective attributes for supplier selection. In that survey, a fuzzy DEMATEL questionnaire was sent to seventeen experts in the electronic industry. The experts were asked about 10 criteria as follows: 1) quality, 2) cost, 3) technology ability, 4) service, 5) delivery, 6) stable delivery of goods, 7) lead-time, 8) reaction to demand change in time, 9) production capability and, 10) financial situation. The questionnaire includes a definition of each criterion for ease of understanding. In the next part of the questionnaire, the correspondents were asked to rank the importance of each factor based on a scale of 1 to 4. Numbers 1, 2, 3, and 4 showed the degree of no importance, low importance, importance, and high importance respectively. The second part was a pair-wise comparison to assess the impact of each score, where scores of 0, 1, 2, 3 and 4 represent no influence, low influence, normal influence, high influence, and very high influence, respectively. The results showed that stable delivery of goods is the most influential and demonstrates the strongest connection to other criteria.

Chamodrakas et al., (2010) proposed an integrated fuzzy programming-based model for supplier selection. The model contains two steps including initial screening of the suppliers through the enforcement of hard constraints on the selection criteria and ranking suppliers through the application of FPP. In the first step, through an accurate method, buyers can decrease the initial set of available suppliers thus alleviating the influence of information overload. In the second part, the FPP was performed to rank the suppliers. The presented model mitigates the information overload influence that is inherent in the environment of electronic marketplaces, provides an easier elicitation of user preferences using the decreasing of essential user input (i.e. pairwise comparisons) and reduces computational complexity in comparison with the original FPP method. Simultaneously, the technique handles inconsistency and vagueness of the preference models of the decision makers by adopting and modifying the FPP method.

Awasthi et al., (2010) proposed a fuzzy multi criteria approach for assessing environmental performance of suppliers. The presented model comprises three stages. The first stage includes identification of attributes for evaluating environmental performance of suppliers. In the second stage, the experts rate the selected criteria and the suppliers against each of the criteria. Linguistic assessments are performed to measure the criteria and the suppliers' performance. These linguistic ratings are then integrated through fuzzy TOPSIS to generate an overall performances score for each supplier. The alternative with the highest score is selected as the best one. In stage three, sensitivity analysis is carried out to assess the effect of attribute weights on the environmental performance evaluation of suppliers. The results proved that the integrated model is very useful for decision making in supplier selection.

Mani, Agarwal, & Sharma, (2014) concentrated on socially sustainable supplier selection through social factors by using AHP in decision making. Govindan et al., (2013a) proposed a fuzzy TOPSIS model for sustainable supplier selection. First, they determined the measures and metrics in each aspect of sustainability. Then after collecting the data set, fuzzy TOPSIS was used to prioritize the suppliers.

Vinodh et al., (2011) proposed a fuzzy analytic network process (FANP) model to rank the best supplier. After selecting evaluation attributes, FANP was applied to select the best supplier. (Bayazit, 2006) used ANP (as an extension of AHP) to evaluate suppliers' performance and select the most suitable supplier. After determining the criteria (quality, on-time delivery, price, flexibility, delivery lead-time, top management capability, personnel capabilities, process capability, financial capability, and market share) the suppliers were ranked through ANP. The author concluded that the ANP enabled decision makers to incorporate multiple criteria and to work with interdependencies between them.

Dou et al., (2014) proposed a gray ANP method to determine green supplier development programs that would improve suppliers' performance. The approach used ANP to determine the weights of attributes and prioritize of green supplier development programs. Afterward, the gray aggregation method was performed to assess suppliers' involvement propensity in different green supplier development programs.

Büyüközkan and Çifçi , (2011) proposed a framework by combining fuzzy logic and ANP to prioritize sustainable suppliers. The model not only assesses the suppliers' performance, but also maintains the consistency level of the assessment. (Galankashi et al., (2015) hybridized Nominal Group Technique (NGT) with fuzzy ANP to select the best supplier with respect to environmental criteria. First, NGT was deployed to determine the most important criteria. Then, fuzzy ANP was used to weight and evaluate the suppliers' performance.

2.2.1.2 Mathematical Programming (MP)

These models including Data Envelopment Analysis (DEA) (Baker et al., 1997; Braglia et al., 2000; Forker et al., 2001), Linear Programming (LP) (Ng, 2008; Talluri et al., 2003, 2005), Multi Objective Programming (MOP) (Narasimhan et al., 2006; Wadhwa et al., 2007), Goal Programming (GP) (Karpak et al., 2001), Integer linear programming (ILP) (Hong et al., 2005; Talluri, 2002), Integer non-linear programming (IN-LP)(Ghodsypour et al., 2001).

DEA is a well-known non-parametric technique that has been successfully performed in supplier selection. (Saen, 2007) proposed a cardinal and ordinal DEA model for selecting supplier efficiency. The model deals with imprecise data. The author showed that the model can be useful for evaluating suppliers' efficiency as well as ranking them. In order to establish an efficient SCM,

Toloo and Nalchigar, (2011) provided a DEA model which considers both cardinal and ordinal criteria. The provided model determines the efficient suppliers by solving one mixed integer linear programming (MILP). Braglia and Petroni, (2000) used the DEA to evaluate suppliers' efficiency in a manufacturing company. After determining inputs and outputs of the system (management capabilities, production facilities and capacity, technological capabilities, financial position, experience, geographical location, profitability, quality, and delivery compliance), the efficiency of 10 suppliers were calculated using different DEA models (Cross-efficiency). Model allows decision makers to rank the suppliers on the basis of their overall performance.

Liu et al., (2000) presented a simplified DEA model to assess the general efficiency of suppliers according to three input and two output attributes. The purpose of the model was to select a supplier having higher supply variety so that the number of suppliers can be reduced. Narasimhan et al., (2001) performed DEA model to assess potential suppliers for a multinational corporation in the telecommunications industry.

11 selection criteria were taken into account in the model (six inputs and five outputs). Based on the efficiency value, the suppliers were classified into four categories: high and efficient performers, high and inefficient performers, low and efficient performers and low and inefficient performers.

Talluri et al., (2002) proposed a three-phase DEA model. In the first part, suppliers, manufacturers, and distributors were assessed through DEA. On the basis of the efficiency numbers derived from the first part and the optimal scores of stakeholders to be used calculated in the second stage, the optimal routing of material from selected suppliers to manufacturers to warehouses were identified (W. Ho et al., 2010).

Dobos et al., (2014) used Data Envelopment Analysis (DEA) to assess the performances of suppliers on the basis of environmental criteria. Talluri et al., (2003) proposed two linear models to maximize and minimize the efficiency of a supplier against the best target measures set by the buyer. Determining both maximum and minimum efficiencies of each supplier would enable an in-depth understanding of a suppliers' performance. Talluri et al., (2005) also presented a linear model to assess and choose potential suppliers based on the strengths of existing suppliers. To validate the model, the results derived from the proposed model were compared with advanced DEA model. Talluri, (2002) modeled supplier evaluation process as a binary integer linear programming model with respect to ideal targets for bid attributes set by the buyer. Hong et al., (2005) developed a combined-integer linear model to select efficient suppliers. Using the model, the optimal alternative of suppliers and optimal order quantity are obtained, thereby maximizing income.

2.2.1.3 Artificial Intelligence (AI)

Artificial Intelligence (AI) approaches including Genetic Algorithm (GA) (Ding et al., 2005), Artificial Neural Networks (ANN) (Lizhe et al., 2012), Support Vector Machine (SVM) (Ren et al., 2009), Adaptive Neuro Fuzzy Inference System (ANFIS) (Sadeghi Moghadam et al., 2008), Fuzzy Inference System (FIS) .

AI-based models have been widely used in many fields of science. These models estimate the relationships between the input(s) and output(s) without the need for prior knowledge about the mechanisms that produced the collected data (Gandomi et al., 2011b). these models are able to provide excellent results with minimal attempts (Metenidis et al., 2004).

AI-based approach is one of the best-known techniques in modeling the suppliers' performance (Vahdani et al., 2012). Using purchasing experts and/or historical data, this technique is able to be designed based on computer aided systems. Numerous pure AI models have been applied for forecasting suppliers' performance (as behavioral modeling).

Chen et al., (2009) proposed an ANN-based model to help managers describe and refresh their specific supplier selection attributes based on changing situations. They found that the approach establishes the supplier selection attributes for different enterprises on the basis of their own circumstances, and once business environment changes, with new data being generated, the set can be refreshed dynamically and timely.

Kuo et al., (2010a) proposed an intelligent supplier decision support system which is able to consider both the quantitative and qualitative criteria. The model enables decision makers to deal with quantitative data such as profit and productivity.

The results prove that the model proposed in this research makes more accurate and favorable judgments in choosing suppliers after considering both qualitative and quantitative factors. Choy et al., (2003) presented an integrated ANN-based model to select and benchmark potential partners of Honeywell Consumer Products Limited in Hong Kong. Lee and Yang, (2009) proposed an ANN-based predictive model with application for forecasting the supplier's bid prices in supplier selection negotiation process.

Güneri, et al., (2011) proposed a predictive ANFIS-based model in supplier selection in the textile industry. They first determined Quality, Cost, Delivery, Relationship Closeness and Conflict Resolution as the appropriate attributes for evaluating the suppliers of the textile firm. Sales of company shares was selected as the output (suppliers' performance) of the problem. A 1-10 numeric scale was applied to rate the criteria. After collecting the dataset, three most effective criteria on the performance were selected and a predictive ANFIS-based model was proposed to estimate the suppliers' performance.

Priyal et al., (2011) modeled supplier's performance through ANFIS. To collect the data set, a questionnaire was provided to rate suppliers' performance. It is worth noting that the criteria for assessing the suppliers' performance were Cost, Quality, Service, Relationship, Organization and Past Relationship respectively. After gathering the data set, ANFIS was used to model the process and to show the validity of the model, some parts of the collected data were dedicated for testing. The results showed the precision of the ANFIS model in predicting the suppliers' performance.

Vahdani, et al., (2012) proposed a predictive AI-based structure for supplier selection in a cosmetic company. They applied a linear neuro-fuzzy model for modeling the suppliers' performance using the defined criteria. First they determined suitable criteria for evaluating the suppliers. Then, they used a numeric scale to rate the selected criteria. In addition, they used the same numeric scale for determining the suppliers' performance. After collecting the historical dataset (about the attributes and the performance), the dataset was divided into two parts for training the neuro fuzzy system and testing the predictive ability of the proposed model. To validate the accuracy of the model in the training process and the testing process, the results obtained by the proposed model were compared with the results obtained by Radial Basis Function (RBF) neural network, Multi-Layer Perceptron (MLP) neural network and Least Square-Support Vector Machine (LS-SVM).

Choy and Lee, (2002) developed a general structure via the CBR approach for supplier evaluation. Assessment attributes were divided into three parts: technical capability, quality system, and organizational profile. The model was applied in a customer manufacturing organization which had stored the performance of past suppliers and their criteria in a database system. The presented model would then retrieve or select a supplier who met the specification predefined by the company most.

Azadnia et al., (2012) integrated an approach of clustering with MCDM techniques to solve sustainable supplier selection problem. First, self- organizing map neural network method has been used for clustering and prequalifying the suppliers on the basis of customer demand criteria and sustainability factors. Afterwards, TOPSIS was utilized in order to rank the cluster of suppliers to enable coordination between the suppliers and customers. A case study was applied to illustrate the efficiency of proposed model.

2.2.2 The integrated approaches

These approaches are divided into three categories including MADM-based models; MP-based models; AI-based models.

2.2.2.1 MADM-based models:

Generally, AHP-based models(Bottani et al., 2008; Yang et al., 2006), ANP-based models (Demirtas et al., 2009; Demirtas et al., 2008) are in this category.Kannan et al., (2013) combined FAHP with TOPSIS to rank suppliers' with respect to environmental attributes. Then, they proposed a linear model for order allocation. They stated that their model is the first model which considers green supplier selection and order allocation. Shaw et al. Shaw et al., (2012) proposed an integrated supplier selection model for developing low carbon supply chain. In that model, the weights of the factors were calculated by FAHP. Then, the weights were applied in fuzzy multi-objective linear programming for supplier selection and quota allocation. The proposed model can help decision makers who are faced with uncertain information.

Rezaei et al., (2014) hybridized conjunctive screening method and fuzzy AHP for selecting the best supplier in the airline retail industry. The presented model is twofold: first, the best criteria are selected using conjunctive screening technique and second, by the application of fuzzy AHP, the best supplier is determined.

Lin et al., (2011) combined ANP, TOPSIS and Linear Programing (LP) to establish a robust model for evaluating and selecting suppliers. By integrating ANP and TOPSIS the final score of each supplier is calculated. The final value of each alternative is the coefficient of objective function of linear programming. Finally, by maximizing the total purchasing value of the linear equation the optimal order quantity is achieved. Dou et al.

2.2.2.2 MP-based models

DEA-Based models(Ramanathan, 2007; Sevkli et al., 2007) and MOP-based models(Amid et al., 2006; Amid et al., 2009) are included in this category.

Azadi et al., (2015) proposed a combined DEA under fuzzy environment to evaluate suppliers' efficiency and to select the best suppliers based on their sustainable attributes. A case study was carried out to show the validity of the model. The case study proved that the proposed model can measure effectiveness, efficiency, and productivity in inexact environments.

Ng, (2008) proposed a linear model to calculate suppliers' performance. The objective of the model was to maximize the suppliers' performance. Like AHP, the model uses experts for defining the relative importance weightings of attributes.

Ghodsypour and O'Brien, (2001) developed an integrated-integer non-linear model to solve the multi-attribute sourcing problem. The model gives the optimal allocation of products to suppliers for minimizing the total annual purchasing cost.

2.2.2.3 AI-based models

This category includes GA-based model (Che, 2010), ANN-based model(Golmohammadi et al., 2009) and SVM-based model (Xu et al., 2009). One of the best factors for evaluating and ranking suppliers is efficiency as an assessment measure. The idea of DEA was introduced by (Charnes et al., 1978) to compute the productivity of each decision making unit (DMU). As a non-parametric technique, DEA has attracted researchers' attention to be used for evaluating and ranking suppliers. However, due to computer problems, limitations related with homogeneity and precision assumptions of DEA, practitioners combined it with AI techniques.

Ozdemir et al., (2009) conducted a study using simple DEA and Multi Layer Perceptron (MLP) ANN in a German iron and steel industry. They categorized 24 suppliers according to six criteria (input/output) namely Material quality (MQ), Discount on amount (DOA), Discount on cash (DOC), Payment term (PT), Delivery time (DT) and Annual revenue (AR) (AR was considered as an output). After getting the result by input oriented DEA, an MLP neural network was constituted to model the efficiency rating of the suppliers.

D. Wu, (2009) used a DEA-ANN model to evaluate as well as select the best suppliers. In that model, both (Charnes, Cooper, Rhodes) CCR and (Banker, Charnes, Cooper) BCC as the two basic method of DEA were combined with MLP neural networks for estimating the efficiency and to rank the suppliers. The productivity of 23 suppliers was calculated with respect to quality management practices and systems, documentation and self-audit, process/manufacturing capability (PMC), management of the firm, design and development capabilities, cost reduction capability, quality, price, delivery, cost reduction performance, among others. To show the accuracy of the model, a five-fold cross-validation was carried out. Finally, the result obtained by DEA-ANN was compared with DEA-Decision Tree (DT) model. The study concluded that DEA-ANN is more accurate than DEA-DT.

Çelebi et al., (2008) combined CCR DEA with ANN to cope with the shortcoming related with homogeneity and precision assumptions of DEA. They evaluated the suppliers based on cost, quality, delivery and service. Shi et al., (2010) combined CCR-DEA model with Back Propagation (BP) neural network to evaluate and predict suppliers' performance. After collecting the data set from the industry, they calculated each supplier's efficiency through CCR model. Then, using BP neural network the best pattern for forecasting was provided. To validate the model, cross validation was used. The finding represented that the hybrid model is useful for supplier selection.

Jiang et al., (2013) hybridized DEA with SVM to decrease the risk of organizations and to find the suitable suppliers. The presented model includes two steps. The first step categorizes the suppliers into efficient and inefficient as computed by DEA. Then the second step applies efficiency scores as a new data set to train SVM model and further to estimate new suppliers' efficiency and classification.

Farahmand et al., (2014) developed an integrated DEA-SVM method to assess suppliers' efficiency. The first step of the model was to determine proper criteria as the inputs and the outputs. Then, the efficiency score of each supplier was evaluated using DEA. After collecting the data set related to the efficiency, through SVM a suitable SVM-based structure was prepared to predict the efficiency score. To show the validity of the model, the results derived from the proposed model were compared with the obtained results from DEA-ANN model. The findings showed that the DEA-SVM model is more accurate than the DEA-ANN model.

Golmohammadi et al., (2009) proposed a neural-based structure for decision making and for selecting the best suppliers. After defining the evaluative criteria using AHP pairwise comparison the data set was collected. Then, the collected AHP-based data set was divided into two parts for training the ANN model and testing its prediction ability. In order to improve the model, mathematical models were defined for measuring each criterion. Afterward, the same operation was done with the new collected data set. The results showed that the improved model is more accurate than the previous model.

Golmohammadi et al., (2009) proposed an integrated AHP-based GA-ANN model to evaluate suppliers' performance. As with the previous model, they collected the data set, and then to structure the pattern, the data set was divided into two parts for training and testing. Özkan et al., (2014) improved the model proposed by (Golmohammadi, 2011) and presented an ANFIS-based model for supplier selection. They highlighted that their model is more accurate than the proposed neural network model.

Over the past decade, numerous models have been developed for supplier evaluation and selection. Table 2.1 summarizes the existing decision making models in the field of supplier selection.

Table 2.1: Summary of the existing techniques for supplier selection

Category	Technique	Application Area	Author(s)
MCDM-based models	AHP-based models	Supplier selection; sustainable supplier selection; supplier selection; sustainable supplier selection; supplier selection	(Bhattacharya et al., 2010); (Gold et al., 2015); (Rezaei et al., 2014); (Mani et al., 2014);(Deng et al., 2014)
	TOPSIS-based models	Supplier selection; supplier selection; supplier selection	(Wood, 2016); (Beikkhakhian et al., 2015); (Rouyendegh et al., 2014)
	ANP-based models	Supplier selection; green supplier selection; supplier selection	(Dargi et al., 2014); (Büyüközkan et al., 2012); (Bruno et al., 2016)
	DEMATEL	Carbon management-green supplier selection; supplier selection; supplier selection	(Hsu et al., 2013); (Dey et al., 2012); (Dey et al., 2012)
	ELECTRE	Supplier selection; selection; supplier selection; selection; supplier selection	(Karsak et al., 2015); (Montazer et al., 2009); (Kar, 2014)
	VIKOR	Supplier selection; green supplier selection; supplier selection	(Karsak et al., 2015); (Akman, 2014); (Shemshadi et al., 2011)

Table 2.1: Continued

	Simple multi-attribute rating technique (SMART)	Supplier selection;	(Seydel, 2005);
Mathematical Programing	DEA	Green supplier selection; supplier selection; sustainable supplier selection	(Dobos et al., 2014); (Karsak et al., 2014); (Azadi et al., 2015)
	LP	Supplier selection;	(Nazari-Shirkouhi et al., 2013)
	MOP	Supplier selection; green supplier selection; supplier selection	(Nazari-Shirkouhi et al., 2013); (Kannan et al., 2013); (Shaw et al., 2012)
	ILP	Supplier selection;	(Manzini et al., 2015)
	IN-LP	Supplier selection;	(Ware et al., 2014)
Artificial Intelligence	ANN	Supplier selection; supplier selection;	(Golmohammadi, 2011); (Golmohammadi et al., 2009)
	ANFIS	Supplier selection;	(Güneri et al., 2011)
	FIS	Sustainable supplier selection; supplier selection;	(Amindoust et al., 2012); (Lima et al., 2013)
	SVM	Supplier selection; supplier selection	(Kong et al., 2013); (Guo et al., 2009)

Generally the literature reports that each model has its own specific merits and demerits (Vahdani et al., 2012). MCDM techniques are easy to use, but they depend heavily on decision makers' opinion. Mathematical programming models are very accurate methods but they cannot work with qualitative attributes. Intelligent based model are very robust and powerful in decision making. Although the AI-based models including pure and integrated methods are very accurate in suppliers' performance evaluation and selection, their main drawback is that they are considered as block box tools not capable of generating a mathematical model for the suppliers' performance with respect to the determined criteria. In this study, the aim is to solve the black box problem in supplier selection process.

2.3 Sustainable supplier selection attributes

One of the main challenges in the supplier evaluation process is to choose the right criteria. The criteria in sustainable supplier selection are determined based on the three aspects known as economic, environmental and social. In economic aspect, literature reports that different criteria have been used for supplier selection.

Dickson's survey (Dickson, 1966) was the first to identify 23 attributes that purchasing agents and managers in the United States and Canada preferred to use for evaluating suppliers' performance. Weber et al., (1991) in 1991 conducted a review of 74 articles published from 1966 to 1990. The authors highlighted that cost/price, delivery and quality were the most important criteria in assessing suppliers. Ho et al., (2010) suggested that the most widely adopted criteria for supplier selection are quality, delivery, price (or cost), manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety and environment respectively. In terms of environmental aspect, Govindan et al., (2013b) carried out a literature review survey and showed that environmental management system is the most widely used environmental criterion followed by green image, environmental performance, design for environment, green competencies, environmental improvement cost, ISO 1400, green product and so on. In terms of social aspect, a number of criteria have been determined which can be summarized as discrimination, long working hours, human rights, health and safety, information disclosure, the rights of stakeholders, employment practices (Amindoust et al., 2012; Azadi et al., 2015; Ghadimi et al., 2014; Goebel et al., 2012; Govindan et al., 2013a; Mani et al., 2014). Table 2.2 summarizes the criteria applied to have SSCM.

Table 2.2: Summary of the sustainability main criteria and sub-criteria

Criteria	Sub-criteria	Application Area	Authors
Quality	Quality-related certificates	Supplier selection; green supplier selection; green supplier selection	(Hsu et al., 2009; Lee et al., 2009; Yuzhong et al., 2007)
	Process capability	green supplier selection	(Yang et al., 2008)
	Quality of material	sustainable supplier selection	(Büyüközkan et al., 2011)
	Quality assurance	sustainable supplier selection; green supplier selection; green supplier selection; green supplier selection; supplier selection; green supplier selection; green supply chain; green supplier selection	(Büyüközkan et al., 2011; Chiou et al., 2008; Kannan et al., 2015; R. Kuo et al., 2010b; Kuo et al., 2012; Li et al., 2009; Tseng, 2011; Yuzhong et al., 2007)
	Capability of handling abnormal quality	Green supplier selection; green supplier selection	(Kannan et al., 2015; Lee et al., 2009)
	Rejection rate of the product	Green supplier selection; green supplier selection	(FeyzioğLu et al., 2010; R. Kuo et al., 2010b)
	Quality assessment	Green supplier	(FeyzioğLu et al., 2010)
	Rate of certified product	Green supplier selection	(Yang et al., 2008)
	Total quality management	Green supplier selection	(Yang et al., 2008)
	Manufacturing process improvement	Supplier selection	(Kuo et al., 2012)
	Extent of Information Standardization	Green supplier selection	(Li et al., 2009)
	Warranties and Claim Policies	Green supplier selection; Green supplier selection	(Kannan et al., 2015; R. Kuo et al., 2010b)
Cost	Material cost	Green supplier selection	(Kannan et al., 2015)
	Transportation Cost	Green supplier selection	(Kuo et al., 2010b)
	Price performance value	Green supplier selection; Green supplier selection	(Kannan et al., 2015; Kuo et al., 2010b)
	Compliance with sectorial price behavior	Green supplier selection	(Kuo et al., 2010b)
	Production cost	Green supplier selection	(Yeh et al., 2011)
	Time Delivery Rate	Green supplier selection	(Li et al., 2009)
	Level of Maintenance Service	Green supplier selection	(Li et al., 2009)
	Service Attitude	Green supplier selection	(Li et al., 2009; Yan, 2009)

Table 2.2: Continued			
Service	Security and Compensation	Green supplier selection	(Li et al., 2009)
	Internal service	Green supplier selection	(Chen et al., 2010)
	Responsiveness	Green supplier selection; Green supplier selection	(FeyzioğLu et al., 2010; Kannan et al., 2015)
	Willingness	Green supplier selection	(Kuo et al., 2010b)
	Information sharing	Green supplier selection	(Yan, 2009)
	Rate of delivery	Green supplier selection	(Kannan et al., 2015; Yan, 2009; Yeh et al., 2011)
	Time to solve complaint	Green supplier selection	(Yang et al., 2008)
	Accurate rate of processing order	Green supplier selection	(Yang et al., 2008)
	Delivery performance	Green supplier selection	(FeyzioğLu et al., 2010)
Service	After service	Green supplier selection	(Yan, 2009)
	Internal service	Green supplier selection	(Chen et al., 2010)
	Level of Maintenance Service	Green supplier selection	(Li et al., 2009)
	Service manner	Green supplier selection	(Yang et al., 2008)
Delivery	Level of technique	Green supplier selection; Green supplier selection; Green supplier selection	(Grisi et al., 2010; Kannan et al., 2015; Yang et al., 2008)
	Capability of product development	Green supplier selection; Green supplier selection; Green supplier selection	(Kannan et al., 2015; Kuo et al., 2010b; Lee et al., 2009; Yang et al., 2008)
	Order fulfil rate	Green supplier selection; Green supplier selection	(Kannan et al., 2015; Kuo et al., 2010b)
	Lead time	Green supplier selection; Green supplier selection; green supplier selection	(FeyzioğLu et al., 2010; Kannan et al., 2015; Kuo et al., 2010b)
	Capability of R & D	Green supplier selection; green supplier selection	(Kannan et al., 2015; Lee et al., 2009)
	Technology level	Green supplier selection; green supplier selection	(Kannan et al., 2015; Lee et al., 2009)
	Flexibility of the supplier	Sustainable supplier selection; green supplier selection	(Büyüközkan et al., 2011; Tseng, 2011)
	Supplier Stock management	Green supplier selection	(Grisi et al., 2010; Hsu et al., 2009; Kannan et al., 2015)

Table 2.2: Continued			
Flexibility		Sustainable supplier selection; green supplier selection; green supplier selection	(Büyüközkan et al., 2011; Chen et al., 2010; Zhang et al., 2003)
Environmental			
Env.Man.S	Env. Policies	green supplier selection; green supplier selection; green supplier selection	(Humphreys et al., 2006; Humphreys et al., 2003; Humphreys et al., 2003)
	Env. Planning	green supplier selection; green supplier selection; green supplier selection	(Humphreys et al., 2006; Humphreys et al., 2003; Humphreys et al., 2003)
	Implement and operation	green supplier selection; green supplier selection; green supplier selection	(Humphreys et al., 2006; Humphreys et al., 2003; Humphreys et al., 2003)
	ISO14001 Certification	green supplier selection; green supplier selection; green supplier selection; green supplier selection	(Humphreys et al., 2006; Humphreys et al., 2003; Humphreys et al., 2003; Yang et al., 2008)
	Environment Efficiency	green supplier selection; green supplier selection	(Grisi et al., 2010; Noci, 1997)
	restriction of hazardous substance (RoHS)	green supplier selection; green supplier selection; green supplier selection	(Kannan et al., 2015; Kuo et al., 2010b; Tseng, 2011)
Green product	Green certification	green supplier selection; green supplier selection	(Kannan et al., 2015; Tseng, 2011)
	Green packaging	Sustainable supplier selection; green supplier selection; green supplier selection; green supplier selection	(Büyüközkan et al., 2011; Chiou et al., 2008; Handfield et al., 2002; Lee et al., 2009)
Green product	Re-manufacture	Sustainable supplier selection; green supplier selection; green supplier selection; green supplier selection; green supplier selection	(Büyüközkan et al., 2011; Chiou et al., 2008; Handfield et al., 2002; Paul Humphreys et al., 2003; Humphreys et al., 2003)
	Green production	green supplier selection; green supplier selection; green supplier selection	(Chiou et al., 2008; Handfield et al., 2002; Kannan et al., 2015)
	Recycle	green supplier selection; green supplier selection; green supplier selection	(Handfield et al., 2002; Humphreys et al., 2003; Humphreys et al., 2003)

Table 2.2: Continued			
Pollution control	Air emissions	green supplier selection; green supplier selection; green supplier selection; green supplier selection; green supplier selection	(Handfield et al., 2002; Humphreys et al., 2003; Humphreys et al., 2003; Kannan et al., 2015; Noci, 1997)
	Waste water	green supplier selection; green supplier selection; green supplier selection; green supplier selection; green supplier selection	(Handfield et al., 2002; Humphreys et al., 2003; Humphreys et al., 2003; Kannan et al., 2015; Noci, 1997)
	Solid wastes	green supplier selection; green supplier selection; green supplier selection; green supplier selection; green supplier selection	(Handfield et al., 2002; Humphreys et al., 2003; Humphreys et al., 2003; Kannan et al., 2015; Noci, 1997)
	Energy consumption	green supplier selection; green supplier selection; green supplier selection; green supplier selection; green supplier selection	(Handfield et al., 2002; Humphreys et al., 2003; Humphreys et al., 2003; Kannan et al., 2015; Noci, 1997)
	Pollution reduction capability	Green supplier selection; green supplier selection	(Humphreys et al., 2003; Humphreys et al., 2003)
	Hazardous wastes	green supplier selection	(Kannan et al., 2015)
Green Image	Ratio of green customers to total customers	green supplier selection	(Lee et al., 2009)
	Social responsibility	green supplier selection; green supplier selection	(Chiou et al., 2008; Lee et al., 2009)
	Materials used in the supplied components	green supplier selection; green supplier selection	(Chiou et al., 2008; Lee et al., 2009)
	Green purchasing capabilities	green supplier selection; green supplier selection; green supplier selection	(Hsu et al., 2009; Noci, 1997; Tseng, 2011)
	Green materials coding and recording	green supplier selection	(Hsu et al., 2009)
	Green management systems	green supplier selection	(Grisi et al., 2010)
Green Innovation	**Green design**	**green supplier selection; green supplier selection; green supplier selection; green supplier selection; green supplier selection**	(**Chiou et al., 2008**; Grisi et al., 2010; Handfield et al., 2002; Hsu et al., 2009; Yang et al., 2008)
	Green process planning	green supplier selection; green supplier selection	(Lee et al., 2009; Tseng, 2011)
	Recycling product design	green supplier selection	(Yeh et al., 2011)
	Renewable product design	green supplier selection	(Yeh et al., 2011)
	Green R & D Project	green supplier selection	(Awasthi et al., 2010)
	Redesign of product	green supplier selection; green supplier selection	(Humphreys et al., 2003; Humphreys et al., 2003)
	Management for hazardous substances	green supplier selection	(Hsu et al., 2009)

Table 2.2: Continued

Hazardous Substance Management	Prevention of mixed material	green supplier selection	(Hsu et al., 2009)
	Process auditing	green supplier selection	(Hsu et al., 2009)
	Warehouse management	green supplier selection	(Hsu et al., 2009)
	Inventory of hazardous substances	green supplier selection	(Hsu et al., 2009)
Green warehousing	Decrease inventory levels	green supplier selection; green supplier selection	(Ray et al., 2006; Zhu et al., 2008)
	Investment recovery (IR) (sale) of excess inventories/ materials	green supplier selection; green supplier selection	(Zhu et al., 2004; Zhu et al., 2008)
	Sale of scrap and used materials	green supplier selection	(Rostamzadeh et al., 2015)
	Sale of excess capital equipment	green supplier selection	(Rostamzadeh et al., 2015)
Eco-design	Reuse of package when design	green supplier selection	(Jun et al., 2010)
	Reduction the use of hazard materials when design	green supplier selection	(Jun et al., 2010)
	Rebuild of products when design	green supplier selection	(Jun et al., 2010)
	Reduction of package when design	green supplier selection	(Jun et al., 2010)
	Recycle, reuse and resume of products when design	green supplier selection	(Jun et al., 2010)
	Re-manufacturing	green supplier selection	(Rostamzadeh et al., 2015)
Green Transportation			
	Environmentally friendly transportation	green supplier selection	(Mahmood et al., 2013)
	Environment-friendly distribution	Green supply chain	(Sarkis, 1999)
	Using a modern eco-efficient transportation fleet like energy efficient vessels and high Euro norms for trucks	green supplier selection	(Rostamzadeh et al., 2015)
	Using Green fuels like low sulfur content, and alternative fuels like liquid natural gas	green supplier selection	(Rostamzadeh et al., 2015)

Table 2.2: Continued			
Social			
Employment Practices	Disciplinary and security practice	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Discrimination	Sustainable supplier selection; Sustainable supplier selection	(Gauthier, 2005; Govindan et al., 2013a)
	Employee contracts	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Equity labor sources		(Bai et al., 2010)
	Diversity	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Flexible working arrangements	Sustainable supplier selection	(Bai et al., 2010)
	Job opportunities	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Employment compensation	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
Health and safety	Health and safety incidents	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Health and safety practices	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
Local communities influence	**Health**	**Sustainable supplier selection; Sustainable supplier selection**	**(Bai et al., 2010; Govindan et al., 2013a)**
	Service infrastructure	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Education	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Cultural properties	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	regulatory and public services	Sustainable supplier selection	(Govindan et al., 2013a)
	Supporting educational institutions	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	economic welfare and growth	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Social cohesion	Sustainable supplier selection	(Bai et al., 2010)
Contractual stakeholders influence	Procurement standard	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	consumers education	Sustainable supplier selection Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)

Table 2.2: Continued

	Procurement standard	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Partnership screens and standards	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
Other stakeholders influence	Decision influence potential	Sustainable supplier selection	(Bai et al., 2010)
	Stakeholder empowerment	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)
	Collective audience	Sustainable supplier selection	(Bai et al., 2010)
	Stakeholder engagement	Sustainable supplier selection; Sustainable supplier selection	(Bai et al., 2010; Govindan et al., 2013a)

The literature reports that there is no published paper which measures the importance and applicability of the sustainability criteria and their corresponding sub-criteria. Indeed, solving this gap can be very useful for the managers of the manufacturing organizations and the researchers. Because they can easily find out which criteria are included in the issues of sustainable supplier selection and which criteria are the most effective attributes to improve the performance of the sustainability of the suppliers. Therefore, this research is aimed at developing a comprehensive list of criteria and their corresponding sub-criteria as well as measuring their importance and applicability.

2.4 Chapter summary

This chapter includes two sub-sections: I) the decision making methods for supplier selection; II) the evaluative sustainability attributes for suppliers' performance assessment. In the first sub-section, the presented methods were categorized. This sub-section was ended with the previous AI models for supplier selection. In the second sub-section, the main criteria and sub-criteria selected for supplier selection in terms of the sustainability were discussed. The literature reports that various criteria have been used in the three economic, environmental and social aspects for the suppliers' performance evaluation. However, there is a lack of research in measuring the importance and applicability the criteria and their corresponding sub-criteria. Also, it can be mentioned that different models have been developed to solve the problem of supplier selection. It is reported that each kind of model has its own advantages and disadvantages. For example, MADMs/MCDMs models are easy to use, but they depend heavily on decision makers' opinion (For instance, different weights could be determined to the different criteria based on the managers idea). Mathematical programming models cause a major problem in using qualitative attributes. In addition, these techniques need exact data set (collecting exact data set in the real world is very difficult). Generally, most of other categories do not consider the interactions among the various factors and also cannot effectively consider risk and uncertainty in estimating the supplier's performance (Vahdani, et al. 2012). However, it has been proved that computer aided techniques (intelligent-based models) have received much attention from researchers for performance evaluation. In this research addition to developing a comprehensive list of applicable and important criteria and sub-criteria, a new intelligent model is proposed for sustainable supplier evaluation and selection.

CHAPTER 3: RESEARCH METHODLOGY

3.1 Introduction

In this part, the research methodology and its relevant subjects that were applied in proposing the GEP method in order to cope with the drawback of the previous predictive AI models for sustainable supplier selection is explained. The proposed model is evaluated by different statistical methods and compared with the existing intelligent methods. In addition, this section presents briefly error measurement factors, methods for model robustness evaluation and source of theoritical information.

3.2 Methodology of research

This study was carried out on the basis of the two important aspects which were obtained from the related literature review including: “which criteria and sub-criteria should be considered for assessing the sustainability” and “what technique to be used for performance evaluation and selection such suppliers”. In order to find the drawbacks of the previous research and develop practical model, various stages should be carried out. The steps of this study are illustrated in Figure 3.1.

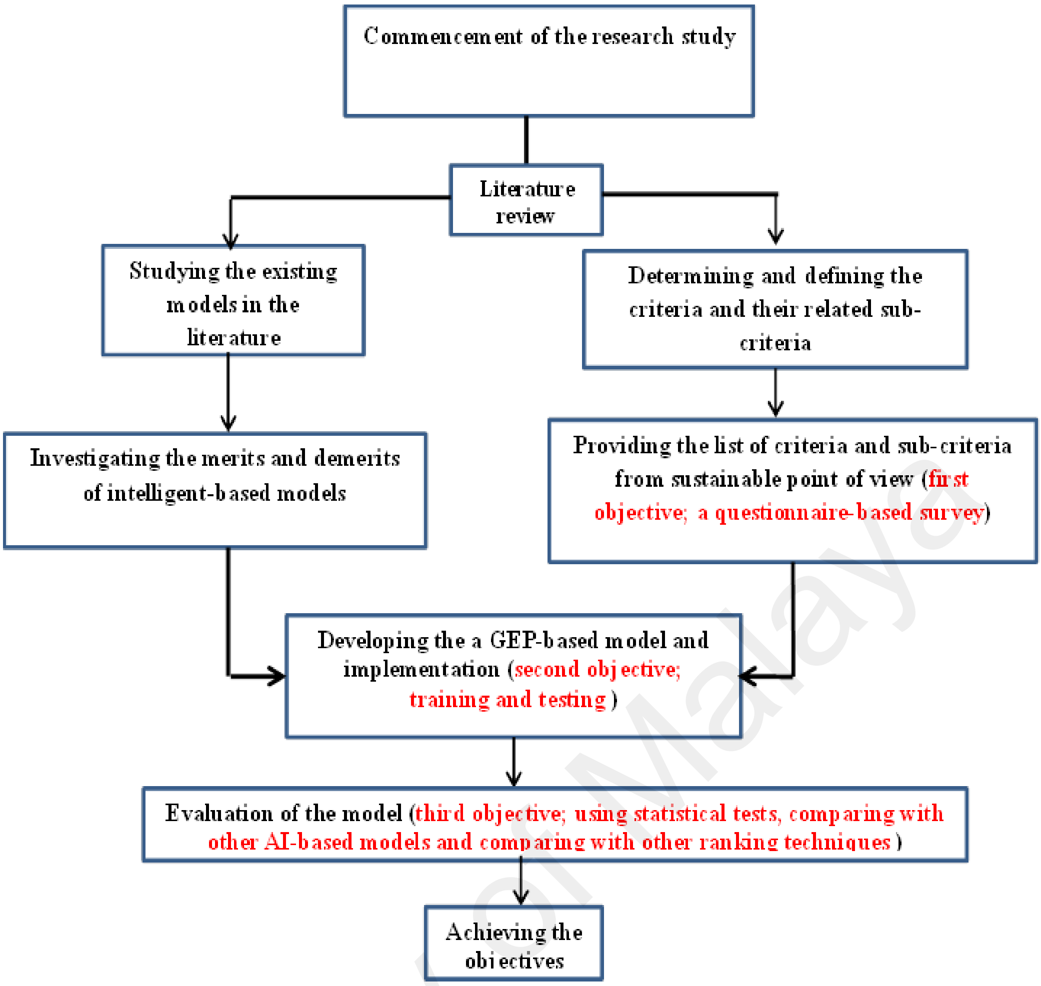

Figure 3.1: The research flow diagram

Figure 3.1 shows the content of the research. In the literature review section, the existing methods are studied as well as the main criteria and sub-criteria in terms of sustainability. In this section, the applied techniques are categorized. Then the merits and demerits of each technique are identified. Also, in the literature review section, the sustainability criteria for supplier selection are divided and their corresponding sub-criteria are determined. In the next stage, the best model and the list of criteria and sub-criteria are provided. In order to show the applicability of the model, the model is implemented in real case studies. Finally, to verify the validity of the proposed model, different performance evaluation tests are investigated.

3.3 Error measurement factors

Reviewing the literature, there were various error measurement factors for evaluating the model. In this section, we present a few instances of the measurement factors that are employed in the proposed model of supplier selection. To do so, the Correlation Determination (R^2) and mean squared error (MSE) are used to indicate the suppliers' performance accuracy.

3.3.1 Coefficient of Determination (R^2)

In statistics, the Coefficient of Determination (Known as R^2) is a value that shows how well data fit a statistical model – sometimes simply a line or a curve. An R^2 of 1 shows that the regression line perfectly fits the data, while an R^2 of 0 shows that the line does not fit the data at all. R^2 has being widely applied to validate the accuracy of predictive models. Its formula is as:

$$R^2 = \frac{(\sum_{i=1}^{n}(h_i-\overline{h_i})\ (t_i-\overline{t_i}))^2}{\sum_{1=1}^{n}(h_i-\overline{h_i})^2 \sum_{i=1}^{n}(t_i-\overline{t_i})^2} \qquad (3.1)$$

where h_i and t_i are, respectively, the actual and predicted output values for the *ith* output, h_i and t_i are, respectively, the average of the actual and predicted performance, and n is the number of suppliers.

3.3.2 Mean Square Error (*MSE*)

MSE is one of the most common measures used in predictive model to validate and show the precision of the developed model. Therefore, the lower the value of *MSE*, the higher is the model accuracy. *MSE* is always a positive number. The formula is:

$$MSE = \frac{\sum_{i=1}^{n}(h_i-t_i)^2}{n} \qquad (3.2)$$

where h_i and t_i are, respectively, the actual and predicted output values for the *ith* output, h_i and t_i are, respectively, the average of the actual and predicted performance, and n is the number of suppliers.

3.4 Evaluating the performance of the proposed models

This section comprises two parts including methods for assessing the robustness of the proposed model. The methods are explained in the following sub-sections.

3.4.1 Statistical methods

The literature shows that to prove the robustness and accuracy of the developed model different established statistical methods have been applied. In the area of Genetic Programming (GP) and its variants such as GEP, Multi Expression Programming (MEP), GP-Simulated Annealing (SA) (GP-SA), etc., (Smith, 1986) statistical conditions have been strongly recommended. The following factors are Smith's conditions for assessing the performance of a predictive model:

I. If a model gives $|R| > 0.8$, a strong correlation exists between the predicted and real values.
II. If a model gives $0.2 < |R| < 0.8$ a correlation exists between the predicted and real values.
III. If a model gives $|R| < 0.2$, a weak correlation exists between the predicted and real values.

In all conditions, the error values (e.g. MSE) should be at the minimum (Mostafavi et al., 2013). In addition, new factors recommended by (Golbraikh et al., 2002) were checked for external validation of the models on the validation data sets. It is recommended that at least one slope of the regression lines (k or k') through the origin should be close to 1 (Mollahasani et al., 2011). It should be noted that k and k' are the slopes of the regression lines between the regressions of actual output (h_i) against predicted output (t_i) or t_i against h_i through the origin, i.e. h_i=$k\ t_i$ and $t_i = k' h_i$, respectively. In addition, the performance indexes of m and n should be less than 0.1 (*m and n* are the two factors for evaluating the model performance). Recently, Roy and Roy (2008) presented a confirmed indicator (R_m) of the external predictability of models. For $R_m > 0.5$, the condition is satisfied. Either the squared correlation coefficient (through the origin) between predicted and experimental values (${R_o}^2$), or the squared correlation coefficient between experimental and predicted values (${R_{o'}}^2$) should be close to R^2 and to 1 (Alavi et al., 2011; Mostafavi et al., 2013; Mostafavi et al., 2014). Also, in order to have an idea of the predictive power of the proposed models, their accuracy is compared with the existing models. The considered validation criteria are given in Table 3.1.

Table 3.1: Statistical factors of the decision model for the external validation

Item	Formula	Condition
1	R	$0.8 < R$
2	$k = \frac{\sum_{i=1}^{n}(h_i \times t_i)}{{h_i}^2}$	$0.85 < k < 1.15$
3	$k' = \frac{\sum_{i=1}^{n}(h_i \times t_i)}{{t_i}^2}$	$0.85 < k' < 1.15$
4	$m = \frac{R^2 - {R_o}^2}{R^2}$	$\lvert m \rvert < 0.1$
5	$n = \frac{R^2 - {R_{o'}}^2}{R^2}$	$\lvert n \rvert < 0.1$
6	$R_m = R^2 \times \left(1 - \sqrt{\lvert R^2 - {R_o}^2 \rvert}\right)$	$0.5 < R_m$
Where	${R_o}^2 = 1 - \frac{\sum_{i=1}^{n}(t_i - {h_i}^o)^2}{\sum_{i=1}^{n}(t_i - \overline{t_i})^2}, {h_i}^o = k \times t_i$ ${R_{o'}}^2 = 1 - \frac{\sum_{i=1}^{n}(h_i - {t_i}^o)^2}{\sum_{i=1}^{n}(h_i - \overline{h_i})^2}, {t_i}^o = k' \times h_i$	

3.4.2 Comparison with other powerful AI-based models (such as ANFIS and ANN)

To show the predictive power of the GEP model, its performance is compared with two powerful soft computing-based models known as ANFIS and ANN (Multi-Layer Perceptron (MLP)).

3.4.2.1 ANFIS

ANFIS is a very powerful predictive intelligent approach, which has been widely used for modeling. The literature related to ANFIS reports that this technique is very accurate to estimate the non-linear relationship between inputs and output(s).

To compare the derived result from the GEP model with ANFIS, the same data set is given to ANFIS and the same process is implemented to simulate the conditions. That is, after collecting the data set, a part of data set is dedicated for training and the rest of the data set is used for testing the algorithm. It is worth noting that the results of the GEP and ANFIS models are compared based on R^2 and MSE.

3.4.2.2 MLP Neural network

Neural network(s) is one of the best methods for analyzing the behavior of a system based on historical data set of the independent variables. Numerous variations of neural networks have been proposed for prediction and modeling. One of the most commonly used networks is Multi-Layer Perceptron (MLP).

To compare the derived result from the GEP model with MLP neural network, the same data set is given to MLP neural network and the same process is implemented to simulate the conditions. That is, after collecting the data set, a part of data set is dedicated for training and the rest of the data set is used for testing the algorithm. It is worth noting that the results of the GEP and MLP neural network models are compared based on R^2 and MSE.

3.4.3 Comparing with other ranking methods (TOPSIS)

Since the GEP-model is used for ranking, the ranking results of the proposed model should be evaluated by comparing with the existing ranking techniques. In this research, to show the ranking power of the GEP model in contrast with other ranking techniques, TOPSIS as one of the widely used ranking methods is performed.

TOPSIS is a MCDM-based model which has been widely used for decision making and ranking in different fields of science. TOPSIS simultaneously calculates the distance to both positive ideal solution and negative idea solution, and the best order is categorized based on their relative closeness, and a combination of these two distance measures. The merits of TOPSIS are as follows: i) It is a simple technique; ii) It takes any kind of attribute; iii) The calculation processes are easy; iv) It is reasonable and logical. To compare the ranking results of the GEP-model with TOPSIS, a new data set is collected. Then the ranking of the suppliers is done using the formula obtained using GEP. Also, the ranking is obtained by applying TOPSIS. Then, the ranking results of the GEP-model are compared with the results computed by TOPSIS.

3.5 Sources of theoretical information

To do a comprehensive literature review, it is needed to use authentic sources of knowledge. Currently, the internet is a very useful tool in obtaining knowledge in different aspects. In this study, various search engines have been applied to download appropriate papers such as ISI web of knowledge, Science direct, Springer, Taylor and Francis, Emerald, and Google. The maximum focus was on ISI web of knowledge, Science Direct, Springer and Taylor and Francis because of the quality of the papers published by them. Also the most of the popular researchers concentrate on these sources. A comprehensive reference about decision making in supplier selection was collected. To find the related papers, key words like "supplier selection", "performance evaluation","artificial intelligence", etc. were used. After downloading the articles, the full text of each paper was studied to find the related papers to our research. Finally, 150 papers from the aforementioned mentioned journals were performed. The theoretical information from internet provided the necessary background and knowledge in relation to the following to main area of the research: 1) Identifying and developing a comprehensive list of criteria and their corresponding sub-criteria; 2) Proposing a new intelligent-based model for performance evaluation by taking into consideration the black box issue (as further explained in the thesis). In author's opinion the abovementioned information have approximately contributed around 60% in this research work.

3.6 Chapter summary

This chapter briefly explains the research methodology in sub-section 3.2. Figure 3.1 illustrates the content of the research. In the third level of the research methodology the first objective of the research is achieved. In the fourth and fifth levels the second and third objectives are obtained, respectively. In addition, this section gives brief overview about the used error measurement factors including R square and MSE (see equations 3.1 and 3.2). In sub-section 3.4 the three different methods were presented for assessing the developed model. The first evaluation method is applying established statistical methods. The second evaluation method is to compare the current intelligent model the existing AI-based models such as ANFIS and ANN. The last evaluation method is to compare the ranking power of the GEP model with the ranking results derived from TOPSIS (as one of the most famous ranking methods in decision making). The last sub-section is sources of theoretical information, which shows that which publishers have been searched in doing this research.

CHAPTER 4: DEVELOPMENT OF A COMPREHENSIVE LIST OF CRITERIA AND SUB-CRITERIA FOR THE EVALUATION OF SUPPLIERS' SUSTAINABILITY PERFORMANCE IN THE MANUFACTURING INDUSTRY

4.1 Introduction

This section presents the methodology to develop a list of important and applicable cirteria and sub-criteria for assessing a supplier's sustainability performance in the manufacturing industry. The following sub-sections include 1) the methodolgy for development of the main criteria and their corresponding sub-criteria; 2) the developed set of criteria and sub-criteria; 3) validation of listed the criteria and sub-criteria.

4.2 The methodology for development of set of the factors for sustainable supplier selection

This part presents the methodology in the development of list of criteria (in each of the aspects of economic, environmental and social) and their corresponding sub-criteria for evaluating suppliers' sustainability performance. Figure 4.1 depicts the process. Initially, the current literature was reviewed to identify some general factors. Other criteria and their corresponding sub-criteria were then identified from conceptual reasoning. Evaluation of the criteria and sub-criteria to establish their importance and applicability through a questionnaire survey was done. Cronbach's alpha and Mann-Whitney U-test were conducted to verify the validity of the survey.

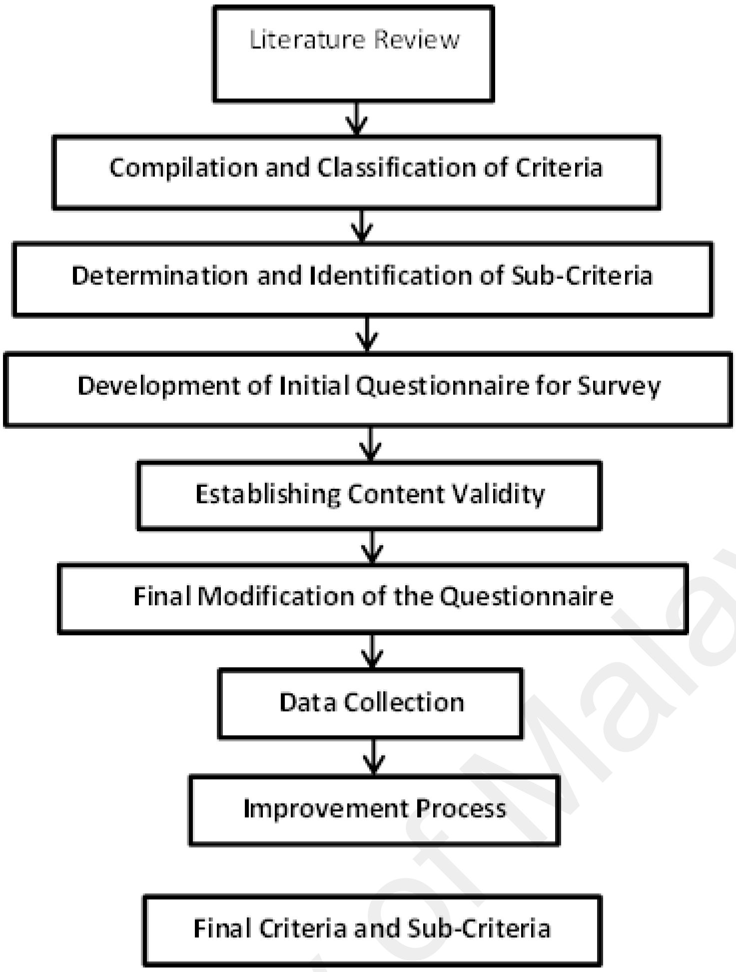

Figure 4.1: The process of developing the criteria and sub-criteria

4.3 The criteria and sub- Criteria for sustainable supplier selection

Following explains the main criteria and their related sub-criteria of each aspect. In this research, 13 main criteria with 46 sub-criteria were selected for the 3 aspects (Amindoust et al., 2012; Azadi et al., 2015; Azadnia et al., 2012; Büyüközkan et al., 2011; Dobos et al., 2014; Govindan et al., 2013a; Kannan et al., 2015; Rostamzadeh et al., 2015; Sarkis et al., 2014; Shen et al., 2013). The following section defines all the main criteria and sub-criteria (Table 4.1 gives the definition of each sub criterion).

4.3.1 The attributes of the economic aspect

In this research, four criteria were selected as the economic attributes such as Cost (C), Quality (Q), Delivery & Service (DS) and Flexibility (F). The definition of each of the main criterion is given in the following section.

4.3.1.1 Cost (C_1):

The factor that shows all the expenditures related to the materials (goods) supplied by supplier. The following sub-criteria were applied in this study for this criterion:

- Material cost ($C_{1,1}$) (Fallahpour et al., 2015; Grisi et al., 2010)
- Freight cost ($C_{1,2}$) (FeyzioğLu et al., 2010; R. Kuo et al., 2010b)
- After sales service cost ($C_{1,3}$) (Yan, 2009)

4.3.1.2 Quality(C_2):

The degree of excellence of supplied materials to meet or exceed purchasers' expectations (Fallahpour et al., 2015). The following sub-criteria were applied in this study for this criterion:

- Rejection Rate of the Product ($C_{2,1}$)(FeyzioğLu et al., 2010)
- Capability of Handling Abnormal Quality ($C_{2,2}$) (Lee et al., 2009)
- Process for Internal Audit quality of Material ($C_{2,3}$) (Grisi et al., 2010)

4.3.1.3 Delivery & Service (C_3):

The factor that shows the effort of supplier in delivering the needed material and solving the problems related the supplied goods to the customer. The following sub-criteria were applied in this study for this criterion:

- Rate of Delivery ($C_{3,1}$) (Yang et al., 2008; Yuzhong et al., 2007)
- After Sales Service ($C_{3,2}$) (Yan, 2009)
- Time to Solve the Complaint ($C_{3,3}$) (Yang et al., 2008; Yuzhong et al., 2007)
- On-Time Delivery ($C_{3,4}$)

4.3.1.4 Flexibility ($\boldsymbol{C_4}$):

The factor that shows the level of the flexibility of supplier in supplying material, price of the supplied material, etc. The following sub-criteria were applied in this study for this criterion:

- Flexibility in Giving Discount ($C_{4,1}$)
- Flexibility of Delivering Time ($C_{4,2}$)
- Flexibility in Ordering ($C_{4,3}$)

4.3.2 The attributes of the environmental aspect

As mentioned before, this study aimed at developing an appropriate list of green criteria and sub-criteria. In this research, six criteria were selected as the environmental attributes such as Environmental Management System (Env.M.S), Green Product (G.P), Green Warehousing (G.W), Eco-Design (Eco.D), Green Technology (G.Te) and Green Transportation (G.Tr). The definition of each of the main criterion is given in the following section.

4.3.2.1 Environmental Management System (Env.M.S) ($\boldsymbol{C_5}$):

The factor that shows the effort of supplier in environment management (Tseng, 2011). The following sub-criteria were applied in this study for this criterion:

- ISO-14001 certification ($C_{5,1}$) (Chen et al., 2010; Chiou et al., 2008; Humphreys et al., 2006; Lee et al., 2009)
- Environmental Performance Evaluation ($C_{5,2}$) (Thongchattu et al., 2010)

- Eco-Labeling (Chiou et al., 2008; Mahmood et al., 2013) ($C_{5,3}$)
- Environment-Friendly Raw Materials ($C_{5,4}$)(Awasthi et al., 2010; Humphreys et al., 2006; Humphreys et al., 2003; Yang et al., 2008)

4.3.2.2 Green product ($\boldsymbol{C_6}$):

The factor that shows the effort of supplier in producing green products. The following sub-criteria were applied in this study for this criterion:

- Green certification ($C_{6,1}$) (Tseng, 2011)
- Reuse ($C_{6,2}$) (Büyüközkan et al., 2011; Handfield et al., 2002; Humphreys et al., 2003; Humphreys et al., 2003)
- Green Packaging ($C_{6,3}$) (Büyüközkan et al., 2011; Chiou et al., 2008)
- Air Emissions ($\boldsymbol{C_{6,4}}$) (Humphreys et al., 2003; Humphreys et al., 2003; Lee et al., 2009; Noci, 1997)
- Waste Water ($C_{6,5}$) (Humphreys et al., 2003; Humphreys et al., 2003; Noci, 1997)
- Hazardous Wastes ($C_{6,6}$) (Kannan et al., 2015)

4.3.2.3 Green warehousing ($\boldsymbol{C_7}$):

The factor that shows the effort of supplier to minimize costs and increase social responsibility by warehousing the raw materials and generally all the needed materials of the companies based on the goal of carbon footprint (Rostamzadeh et al., 2015). The following sub-criteria were applied in this study for this criterion:

- Inventory of Hazardous Substances ($C_{7,1}$) (Hsu et al., 2009; Kannan et al., 2015)
- Inventory of Substitute Material ($C_{7,2}$) (Hsu et al., 2007, 2009)
- Warehouse Management ($C_{7,3}$) (Hsu et al., 2007, 2009)

4.3.2.4 Eco-design (C_8):

The factor that shows the effort of supplier to do the activities that aim to minimize environmental impacts of products during their entire life cycle (Rostamzadeh et al., 2015). The following sub-criteria were applied in this study for this criterion:

- Recycle of Products when Design ($C_{8,1}$) (Bin et al., 2010; Kannan et al., 2015)
- Re-Manufacturing of Products when Design ($C_{8,2}$) (Handfield et al., 2002; Kannan et al., 2015)
- Reduction in the use of Hazard Materials when Design ($C_{8,3}$)) (Bin et al., 2010)

4.3.2.5 Green Transportation (C_9):

The factor that shows the effort of supplier to minimize the environmental pollution while transforming the needed order. The following sub-criteria were applied in this study for this criterion:

- Using a Modern Eco-efficient Transportation fleet like energy efficient Vessels and high Euro norms f or trucks ($C_{9,1}$)) (Rostamzadeh et al., 2015).
- Using Green Fuels like low sulfur content, and alternative fuels like liquid natural gas ($C_{9,2}$) (Rostamzadeh et al., 2015).

4.3.2.6 Green Technology (C_{10}):

The factor that shows the effort of supplier in producing green products (Lee et al., 2009). The following sub-criteria were applied in this study for this criterion:

- Materials Used in the Supplied Components that reduce the impact on natural resources ($\boldsymbol{C_{10,1}}$) (Kannan et al., 2015; Lee et al., 2009) (advantage)
- Capability of R&D ($C_{10,2}$)(Chen et al., 2010; Lee et al., 2009)

  Ability to alter process and product for reducing the impact on natural resources ($C_{10,3}$) (Li et al., 2009)

4.3.3 The attributes of the social aspect

In this research, the social attributes were divided into three parts including Workers' Rights (WR), Health and Safety at Work (HSW), and Supportive Activities for the Workers (SSAW). The definition of each of the main criterion is given in the following section (Bai et al., 2010; Govindan et al., 2013a; Nikolaou et al., 2013).

4.3.3.1 Workers' Rights (C_{11}):

The factor that shows workers have rights at work. The following sub-criteria were applied in this study for this criterion:

- The Workers' contract ($C_{11,1}$)
- Employment insurance ($C_{11,2}$)
- Employment compensation ($C_{11,3}$)
- Standard working hours ($C_{11,4}$)
- The right to sue the employer ($C_{11,5}$)

4.3.3.2 Health and Safety at Work (C_{12})

The factor that shows effort of suppliers to protect the health and safety of workers at work. The following sub-criteria were applied in this study for this criterion:

- Health and safety incidents ($C_{12,1}$) (medical insurance)
- Training for safety at work ($C_{12,2}$)
- Providing appropriate equipment at work ($C_{12,3}$)

4.3.3.3 Supportive Activities (C_{13})

The factor that shows suppliers respect the supportive activities at work. The following sub-criteria were applied in this study for this criterion:

- Discrimination ($C_{13,1}$)
- Growth at work ($C_{13,2}$))
- Wages ($C_{13,3}$)
- Attention to religious and cultural issues at work (such as praying, fasting, etc.) ($C_{13,4}$))

Table 4.1: The definition of the sub-criteria

Economic aspect	
Material cost	The price of the material considering the quality of the material and other services provided by supplier
Freight cost	The cost of transportation
After sales service cost	The price of the after sales service
Rejection rate of the product	Number of rejected supplied goods detected by quality control
Capability of handling abnormal quality	The capability of the supplier in handling abnormal quality problems (Lee et al., 2009)
Process for internal audit quality of material	One shall ensure that the supplier will make a reasonable number of audits on the quality level offered and is certified to ensure a minimum level of quality to prevent possible failures (Grisi et al., 2010)
Lead time delivery	Flexibility in time between the placement and the arrival of an order without compromising quality and cost (Kannan et al., 2015).
After sales service	The level of service is given after delivering goods.
Time to solve the problem	Time between notification to the supplier and solving it
On-time delivery	The capability to follow the predefined delivery
Flexibility in discount	Rate of discount is given by supplier to customer
Flexibility of delivery time	Level of flexibility of supplier in changing the time of delivery of the ordered good
Flexibility in ordering	Level of the flexibility of supplier in changing the orders based on the customers the request of the customer
Environmental	
ISO-14001 certification	Whether the supplier has environment-related certificates such as ISO 1400
Environmental Performance Evaluation	Supplier should have environmental policies, planning of environmental objectives, checking and control of environmental activities (Grisi et al., 2010)
Eco-Labelling	Whether the supplier uses eco-labels for the products
Environment-friendly raw materials	Supplier must use environment friendly materials and avoid to use those materials are not biodegradable.
Green certification	Supplier must provide green related certificates for products (Kannan et al., 2015)
Re-use	Ability to achieve the used products and their related accessories (Kannan et al., 2015)
Green packaging	The level of green materials used in packaging (Kannan et al., 2015; Lee et al., 2009)
Air emissions	The quantity control and treatment of hazardous emission, such as SO2, NH3, CO andHC1(Lee et al., 2009)
Waste water	The quantity control and the treatment of waste water (Kannan et al., 2015)
Hazardous wastes	Pollution minimization initiatives related to Hazardous wastes.

Table 4.1, continued	
Inventory of hazardous substances	Compliance with regulations of hazardous substances to prevent the products from containing exceed in restricted substances (Kannan et al., 2015)
Inventory of substitute material	Supplier must transit their materials into green materials under a fixed deadline to make sure a currently used non green material is replaced by a green material of the same functions and specifications
Warehouse management	Level of warehouse management to prevent material mixing and maintain the quality of material
Recycle of products when design	Ability to treat the used products or their accessories, to reprocess the materials, and to replace the required new materials when producing new products (Rostamzadeh et al., 2015).
Re-manufacturing	Detach certain accessories from waste products for future usage (Rostamzadeh et al., 2015).
Reduction of the use of hazard materials when design	Supplier must try to decrease rate of hazardous material when design
Using a modern eco-efficient transportation fleet	Supplier should use eco-efficient transportation fleet like energy efficient Vessels and high Euro norms f or trucks (Rostamzadeh et al., 2015)
Using Green fuels	Supplier should use Green fuels like low sulfur content, and alternative fuels
Materials used in the supplied components that reduce the impact on natural resources	The use of materials in the components that has a lower impact on the natural resources (Kannan et al., 2015; Lee et al., 2009)
Capability of R&D	Capability of R&D of the supplier to meet current and future demand of the company
Ability to alter process and product for reducing the impact on natural resources	The ability of the supplier to alter the process and product design in order to reduce the impact on the natural resources (Kannan et al., 2015)
Social	
Contract	Supplier should have contract with their workers
Employment insurance	Supplier should provide employee insurance for their workers
Employment compensation	Suppliers should be responsible for their workers
Standard working hours	Ordinary hours are a worker’s normal and regular hours of work, which do not attract overtime rates.
Overtime pay	Supplier should pay the salary for the overtime
Health and safety incidents	Suppliers must provide workers' health and safety in the workplace
Training for safety at work	To prevent accidents and protect the health of workers, they must be trained at work
Providing standard equipment at work	To prevent accidents and protect the health of workers, they must have appropriate equipment
Discrimination	There must not be any difference between men and women workers for growth at work

Table 4.1, continued	
Growth at work	Based on experience and skill workers' position should be changed at work
Wages	Workers' must be paid based on work laws
Attention to religious and cultural issues at work (such as praying, etc.)	Supplier must respect religious and cultural issues at work

*please note that the names of some sub-criteria have been shortened.

4.3.4 Validation of the provided set of criteria and sub-criteria

In order to validate the proposed criteria and their sub-criteria, a questionnaire-based survey was conducted. A questionnaire was developed for evaluating the importance and applicability level of the criteria and their sub-criteria. The questionnaire involves four sections as shown in Appendix A. The first part includes questions for obtaining the background of the respondents (see appendix B). The second, third and fourth parts consist of the economic, environmental and social criteria and their sub-criteria, respectively. In the second part, there are four criteria namely cost, quality, delivery and service and flexibility. Addition to these four criteria, there are thirteen sub-criteria for evaluating each criterion. The third part consists of six criteria and twenty one sub-criteria. The forth part contains three criteria and twelve sub-criteria. The respondents were asked to assign a number to each sub-criterion to assess their importance and applicability level for sustainable supplier selection. Importance level represents the degree of perceived importance placed on the sub-criteria, while applicability shows whether they can be applied or used in practice. A Likert scale from 0 to 5 was performed where 0 = no idea, 1 = very low, 2 = low, 3 =moderate, 4 = high, and 5 = very high.

After the questionnaire was developed, it was sent to seven experts[1] (see appendix C) from academia and industry to conduct content validation to ensure that the contents were evaluating what they are intended to obtain. The comments (see appendix D) and feedback from the experts were applied to revise the questionnaire. After the revision, the questionnaires were sent back to the same experts and they all indicated their agreement.

After finishing the development of the questionnaire, it was sent to 150 experts from academia and industry chosen as potential experts to evaluate sub-criteria. All the responses were received within 35 days[2] from the starting date. The selected academics were based on their expertise and contributions in the field of SCM. On the other hand, experts from the manufacturing industry were selected based on their position and number of years of experience in the supply chain. This list includes experts from Asia, North America, Europe and Australia.

Of the 150 questionnaires mailed, 23 were completed and returned, representing 15.33% of the overall sample. By comparing this percentage with the two of the most cited research works regarding measuring the importance and applicability of the attributes in the field of SCM (Gunasekaran et al., 2004; Olugu et al., 2011), it can be mentioned that this is a suitable level. In the research done by (Gunasekaran et al., 2004) (1591 cited), this level is 14% (1.33% less than the level of this research) and in

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[1]By checking (Olugu et al., 2011), as one of the most cited research works regarding measuring the importance and applicability of the attributes in the field of SCM, it is seen that the number of the experts used in that research is five. Therefore, it can be mentioned that seven experts for content validation is enough in the current research.

[2] No deadline had been given to the respondents. However, the last revised was received after 35 days. After that I did not received any more respond.

the research carried out by (Olugu et al., 2011) (146 cited), this level is 16.5% (1.17% more than this research).

As mentioned above, the respondents were asked to evaluate the sub-criteria, hence, an average mean value was used for each of the criteria to show their level of importance and applicability. The results are presented in the Figures 4.2 to 4.7.

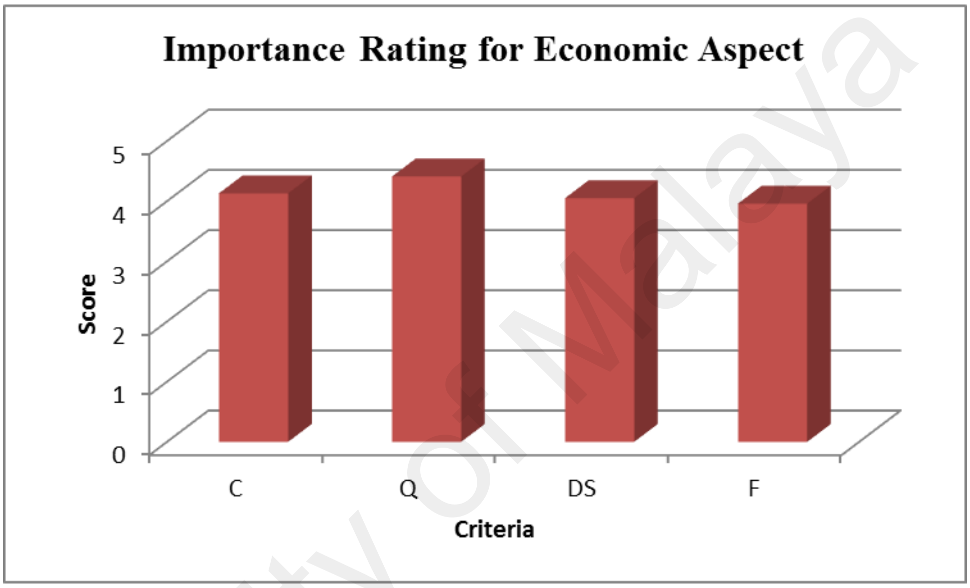


Figure 4.2: The mean importance scores for economic aspect

It can be seen from Figure 4.2 that in economic aspect, Quality had the highest score of 4.41, which implied a 88.2% importance. This was followed by Cost – 4.13, Delivery & Service – 4.05, Flexibility – 3.96, with an importance percentage of 82.6%, 81.0% and 79.2%, respectively.

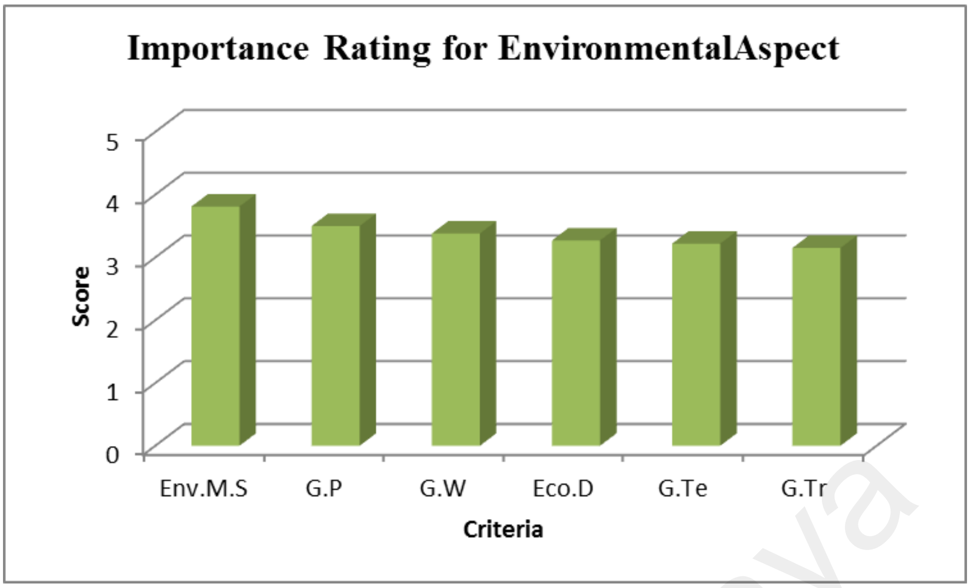


Figure 4.3: The mean importance scores for environmental measures

Figure 4.3 shows that in environmental aspect, Environmental management system had the highest score of 3.81, which implied a 76.2% importance. This was followed by Green Production – 3.5, Green Warehousing – 3.38, Eco-design – 3.27, Green Technology– 3.22, and Green Transportation- 3.15with an importance percentage of 70.00, 67.6 , 65.4, 64.4%, and 63.00% respectively.

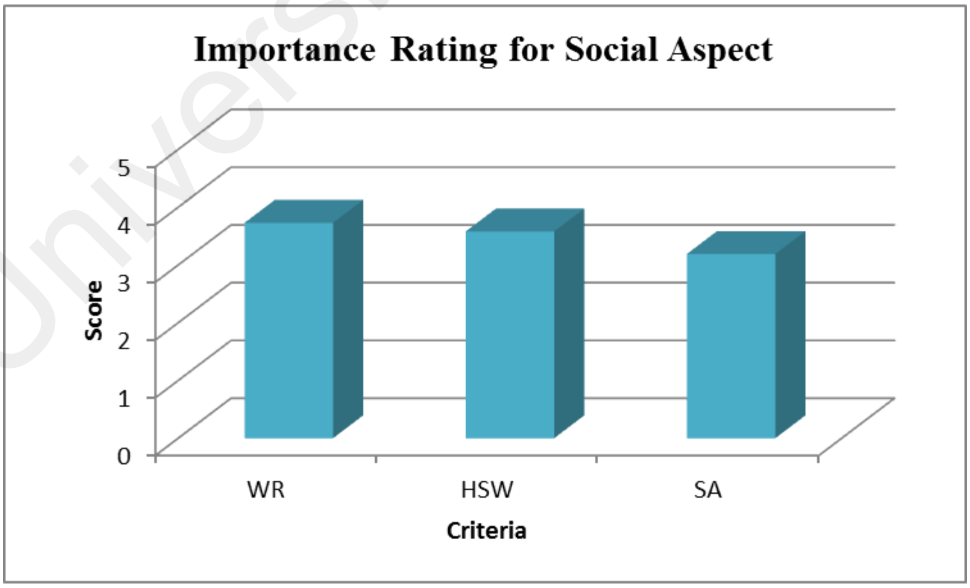


Figure 4.4: The mean importance scores for social measures

Figure 4.4 shows that in social aspect, Workers' Rights (WR), had the highest score of 3.73, which implied a 74.6% importance. This was followed by Health and

Safety at Work (HSW) – 3.58, and, Supportive Activities (SA)– 3.19, with an importance percentage of 71.6, and 63.8%, respectively.

In terms of applicability, the findings are represented in Figures 4.5 to 4.7 for the economic, environmental and social aspects, respectively. As can be observed in Figure 4.5, Quality ranked the highest in applicability with a score of 4.39. This was followed by Cost – 4.32, Delivery & Service – 4.09 and Flexibility– 3.85. It can be observed from Figure 4.6 that for environmental aspect, Environmental Management System had the highest score of 3.81. This was followed by Green Production (GP) – 3.73, Green Warehousing (GW) – 3.52, Eco-design (Eco) – 3.41, Green Technology (GTr)– 3.40, and Green Transportation (Gte) 3.26 with an importance percentage of 70.00,67.60 , 65.40, 64.40%, and 63.00% respectively. Figure 4.7 shows that in social aspect, Workers 'Rights (WR), had the highest score of 4.07. This was followed by Health and Safety at Work (HSW) – 3.79, and, Supportive Activities (SA)– 3.66.

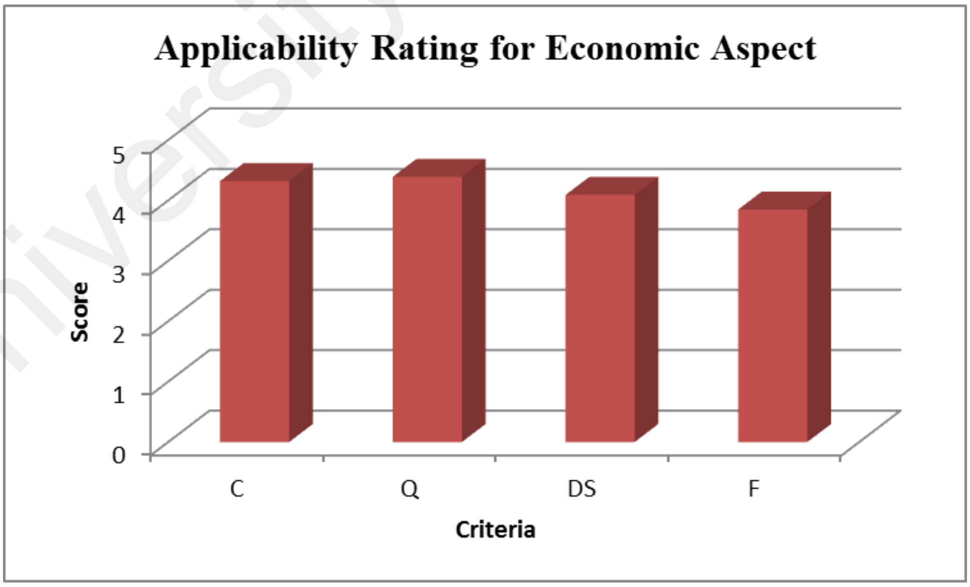


Figure 4.5: The mean applicability scores for economic aspect

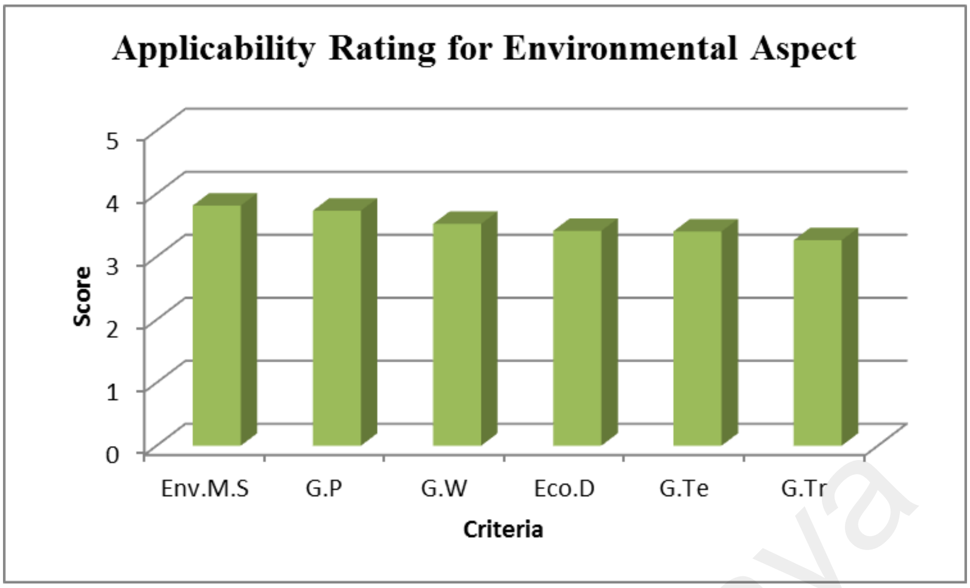


Figure 4.6: The mean applicability scores for environmental aspect

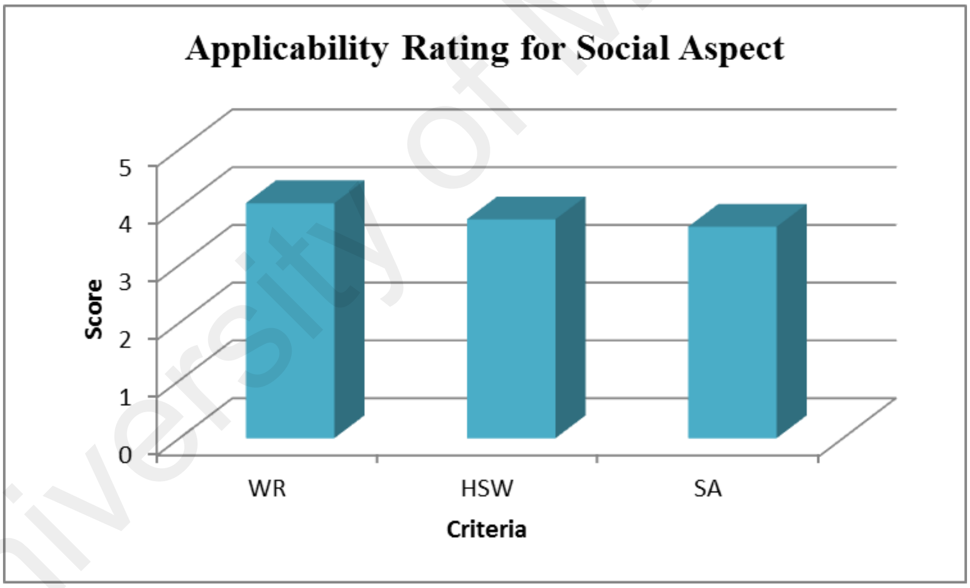


Figure 4.7: The mean applicability scores for social aspect

The findings show that all the criteria obtained a mean importance score of more than 3.1. The most important criterion is quality. This represents that the quality must be considered first sustainable supplier selection. This is in line with the assertions stated by (Govindan et al., 2015; W. Ho et al., 2010). Cost and delivery & service were also highly ranked. This implies that these two criteria have a great impact on sustainable supplier selection. Another attribute that was highly ranked is flexibility. This states that flexibility is an important issue for sustainable supplier selection. Other criteria which showed a considerably high rank are environmental management system, workers' right and health and safety at work. In terms of applicability, all the criteria showed a relatively high score of at least 3.2 which shows that they are all applicable for suppliers' sustainability performance in manufacturing industry. The most applicable criterion is quality, followed by cost, delivery and service and workers' right. Generally the results show that criteria such as flexibility, environmental management system, health and safety at work, and green production received relatively similar scores.

It is worth noting that after gathering the data set, the reliability test was carried out to make sure that the instrument and the data collected are reliable for further analysis. According to the literature "Cronbach's alpha is the most widely used to measure for showing lower or higher guaranteed level of the internal reliability of indicators for a specific scale". Both importance and applicability have thirteen (13) criteria for economic, environmental, and social aspects. All criteria underwent an internal reliability assessment using Cronbach's internal reliability coefficient alpha. The test was run in two stages; the first stage was to test the reliability of the importance of the data set and the second stage was carried out to test the reliability of the applicability of the data set.

Table 4.2: Reliability Test (Cronbach's alpha values)

	Importance	Applicability
C	0.817	0.793
Q	0.801	0.823
DS	0.814	0.46
F	0.843	0.861
Env.M.S	0.907	0.873
G.P	0.769	0.856
G.W	0.9	0.789
Eco.D	0.823	0.866
G.Te	0.808	0.844
G.Tr	0.787	0.879
WR	0.849	0.784
HSW	0.833	0.8
SA	0.761	0.919

In terms of importance of the data set, the results of running an internal reliability assessment test using Cronbach's alpha revealed 13 to have yielded alpha values greater than recommended value of 0.70 as suggested by others (Ferketich, 1990). Applicability data set has shown alpha values after running an internal reliability assessment test using Cronbach's alpha. These values are also considered above recommended value of 0.70. Table 4.2 shows the results of alpha values for both importance and applicability data sets.

Another statistical analysis, Mann–Whitney U-test was used to assess whether the mean scores of the two sets of data (importance and applicability) differ significantly (Ho = the importance and applicability of the criteria should be statistically the same). SPSS software was applied to conduct this non-parametric test. Since the Mann–Whitney U-test is done on ranked scores, the data for the two groups do not have to be normally distributed (Olugu et al., 2011). All the main criteria of the three aspects were assessed using this test and the *p* value of each of them was greater than 0.05 (a *p* value of less than 0.05 means there is a significant difference between the data sets). The results presented in Table 4.3 show that there is no significant difference between the mean scores of the two data sets. Therefore, it can be said that there is a strong correlation between the importance and applicability of the listed criteria.

Table 4.3: The results of Mann-Whitney U-test for importance and applicability

	P-Value	**Importance**	**Applicability**
C	0.521	4.13	4.39
Q	0.66	4.41	4.32
DS	0.179	4.05	4.09
F	0.74	4.96	3.85
Env.M.S	0.173	3.81	3.81
G.P	0.209	3.5	3.73
G.W	0.092	3.38	3.52
Eco.D	0.127	3.27	3.41
G.Te	0.231	3.22	3.4
G.Tr	0.831	3.15	3.26
WR	0.165	3.37	4.07
HSW	0.357	3.58	3.79
SA	0.457	3.19	3.66

4.4 Chapter summary

This chapter developed a comprehensive list of sustainable criteria and sub-criteria for evaluating suppliers' performance as well as measuring their importance and applicability in the real world. The sustainability criteria and their corresponding sub-criteria were categorized into three main aspects (economic, environmental and social).

Each criterion (see sub-sections 4.3.1 to 4.3.3) and their sub-criteria (see Table 4.1) were defined. To measure their importance and applicability, a questionnaire-based survey was carried out (see Figure 4.2 to 4.7). The findings show that still economic criteria are the most essential factors and it is followed by environmental criteria and social criteria. Among the economic-based criteria, quality is the most important attribute. It is followed by cost and delivery and service.

The validity of the survey was proved by different statistical tests (Cronbach's Alpha and Mann–Whitney U-test). Cronbach's Alpha was performed to show the reliability of the data set. Table 4.2 shows the results of alpha values for both importance and applicability data sets. It seems that the alpha value for each criterion in both importance and applicability is greater than 0.7 which means the results are satisfactory. Another statistical analysis, Mann–Whitney U-test was used to assess whether the mean scores of the two sets of data (importance and applicability). Table 4.3 shows that there is no significant difference between the mean scores of the two data sets.

CHAPTER 5: THE DEVELOPED INTELLIGENT MODEL FOR SUSTAINABLE SUPPLIER SELECTION

5.1 Introduction

This research study has developed intelligent-based model for sustainable supplier selection. In this model, Gene Expression Programming (GEP), as a new variant of Genetic programming (GP), has been used to satisfy the objectives of the study (refer to section 1.3.2). Below, the shortcomings of the previous models and the aims of the proposed model are shown first, followed by the assumptions of the developed model. Afterward, a brief review of GEP approach is presented. Considering that in this research ANFIS and Multi-Layer Perceptron (MLP) ANN are used for comparison with the GEP-based model and to validate the robustness of the current model in terms of predictive ability, the basics of the ANFIS and MLP-ANN are reviewed in the following section. In addition, in order to show that the GEP model is reliable in ranking, TOPSIS as one of the well-known ranking methods is used to compare the results. Thus, in section 5.8, a brief review of TOPSIS is presented. Next, the proposed model is described in detail. Finally, the provided model is implemented in a real case company.

5.2 Shortcoming of the previous studies

Predictive AI approach (such as ANFIS, ANN, SVM, etc.) is one of most well-known techniques among the MCDM methods. AI has been successfully used in finding non-linear relationship between variables as described in section 2.2.1.3. However the literature reports that it has not been used much for assessing suppliers' performance, although previous researchers claimed that their models facilitate the procedure of supplier evaluation for decision makers and can select the most suitable suppliers in a minimal time. However, some issues still cannot be addressed:

- What is the point of using an intangible structure which only estimates the performance without any equation?

- How can the provided intelligent-based structure facilitate the supplier evaluation process for managers if the existing AI technique strongly needs special knowledge?

- How can the managers analyze the behavior of the suppliers when they do not know what kind of mathematical relationship exists between the performance and determined criteria?

5.3 Aims of the proposed model

The main purpose of this study is to design an intelligent decision model using GEP to solve the previous drawback of the existing AI models in the pertinent literature as well as providing a list of important and applicable attributes. The proposed intelligent model provides a strategic and open-ended mathematical model to evaluate the performance on the basis of the determined attributes and is used for the ranking in the future without decision makers' judgment effort.

5.4 Model assumption of this model

In order to explain this model, the following assumptions have been made:

1) The model is suitable for suppliers' performance evaluation in any industry based on any kind of criteria (economic, environmental, and social).
2) The model is considered an open-ended model for performance evaluation.
3) The model is applicable with any size of company (Large, Medium, and Small)
4) The model is suitable for strategic decisions

5.5 The used scale for measuring the criteria and sub-criteria and the performance

In this research, a 1-5 Likert scale is used for measuring the criteria where 1 = very low, 2 = low, 3 = moderate, 4 = high, and 5 = very high. Based on the questionnaire, the manager is asked to measure the sub-criteria. Then, the rounded mean value is used as the final number of the main criterion. For example, if Z is a main criterion which has five sub-criteria including a=2, b=4, c=4, d=3, and f=5, the value of Z is $\frac{(2+4+4+3+5)}{5} = 3.6 \approx 4.$ Please note that the final data set used for modeling by GEP includes values for the main criteria. For measuring the performance, a 1-7 Likert scale is used where 1 = very bad, 2 = bad, 3 = moderately bad, 4 = moderate, 5 = moderately good, 6 = good, and 7 = very good.

5.6 Gene Expression Programming

Koza, (1992) first invented GP as an extension of Genetic Algorithm (GA) inspired by Darwinian evolutionary theory, which automatically generates mathematical models. The basic difference between the GA and GP approaches is that GA presents the solution as a string of numbers and GP solutions are computer programs represented as tree structures and expressed in a functional programming language (Güllü, 2014; Mollahasani et al., 2011; Mousavi et al., 2014; Rashed et al., 2012; Zhao et al., 2012) . There are three types of GP known as tree-based GP, linear-based GP and graph-based GP (Figure 5.1) (Luo et al., 2012). Of the three, Linear-based GP has received the most attention.

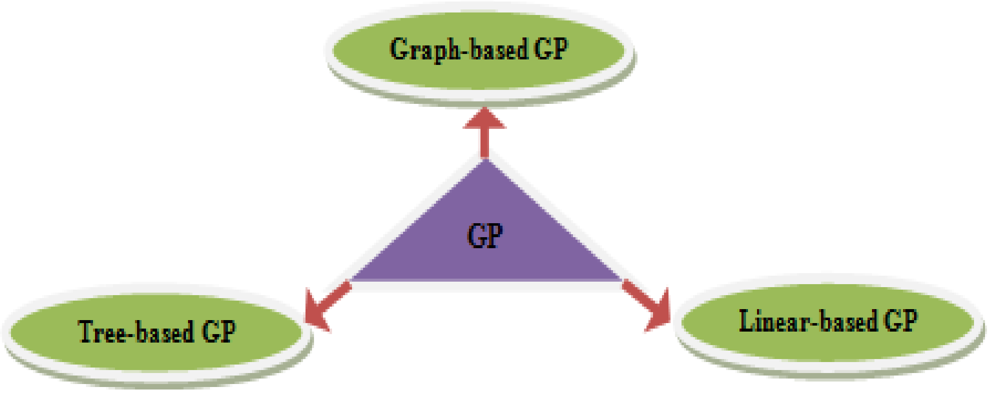


Figure 5.1: Different types of GP

GEP as a robust linear GP-based approach was introduced by Ferreira (Ferreira, 2001). GEP requires five elements: Functional set, terminal set, fitness function, control parameters, and termination condition to develop a model. In the GEP algorithm, strings with a fixed length of characters are used to represent solutions to the problems, which are afterwards expressed as Expression Trees (ETs) of different sizes and shapes. Due to the multi-genic nature of GEP, more complex programs composed of several subprograms will be allowed to be generated during the evolutionary process (Mollahasani et al., 2011). A GEP gene includes a list of symbols which are components from functional or terminal sets like {+, $-$, ×, /, *cos*} and the terminal set like {*a*, *b*, *c*, -*4*} (Alavi et al., 2011b; Alavi et al., 2013). A typical GEP gene is as bellow:

$$\underline{+.\times.cos.a.-}.+.+.\times\ b.a.c.-4.b.a \qquad (5.1)$$

The above expression is termed as Karva notation or *K*-expression (Alavi et al., 2013; Mollahasani et al., 2011). A *K*-expression can be illustrated by a diagram which is an ET. For instance, Figure 5.1 shows the expression tree of the above sample gene.

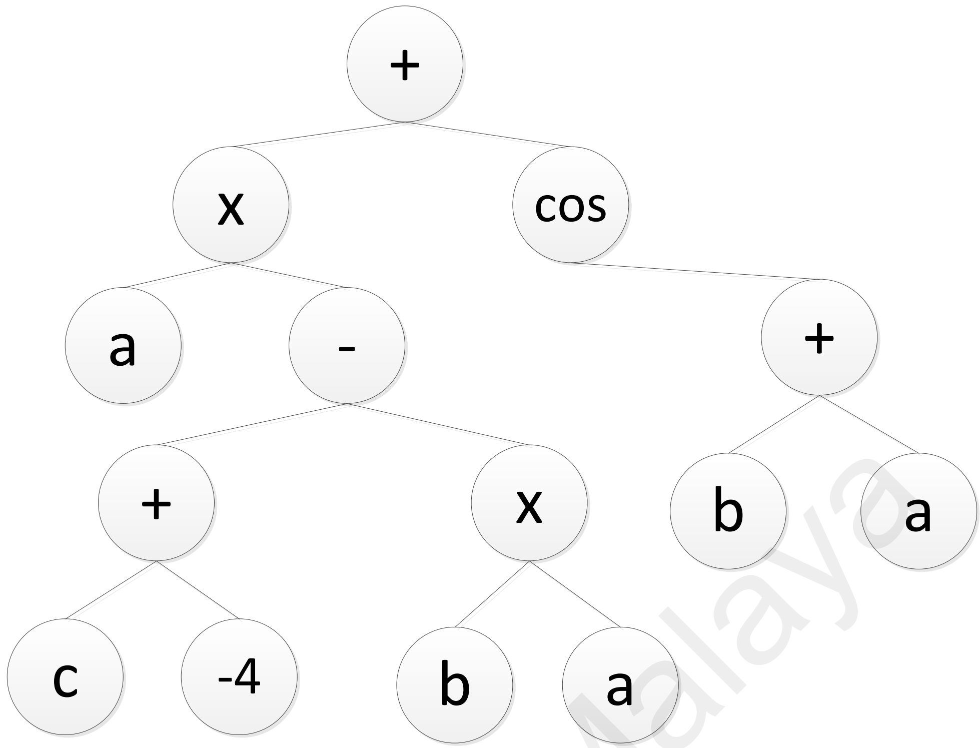


Figure 5.2: Example of expression trees (ETs).

The transformation process is created from the start position in the K-expression, which corresponds the root of the ET, and reads through the string one by one (Alavi et al., 2011c).The mentioned GEP gene can be represented in a mathematical equation as:

$$a\big((c-4)-(b\times a)\big)+cos(b+a) \tag{5.2}$$

There are four steps in GEP to obtain a terminal condition(Ferreira, 2001):

I. Random generation of a fixed-length chromosome of each individual for the initial population.

II. Expressing chromosomes as ETs and evaluating fitness of each individual.

III. Selecting the best individuals according to their fitness to reproduce with modification.

IV. Repeating the above process for a definite number of generations or until a solution has been found.

Based on fitness by roulette wheel sampling with elitism, in GEP, the individuals are selected and copied into the next generation. This guarantees the survival and cloning of the best individuals to the next generation. Using various combinations of genetic operators, variation in the population is introduced. These operators include crossover, mutation and rotation (Ramos et al., 2013). The rotation operator is applied to rotate two subparts of an element sequence in a genome with respect to a randomly chosen point (Ferreira, 2001; Alavi et al., 2011). This can also significantly reshape the ETs. For example, the following gene rotates the first five elements of gene (1) to the end:

$$+.+.\times b.a.c.-4\underline{.b.a.+.\times.cos}.a. \tag{5.3}$$

The solution function is built using only the first seven elements$(b+a)+(c\times -4)$, with the corresponding expression illustrated in Figure 5.3.

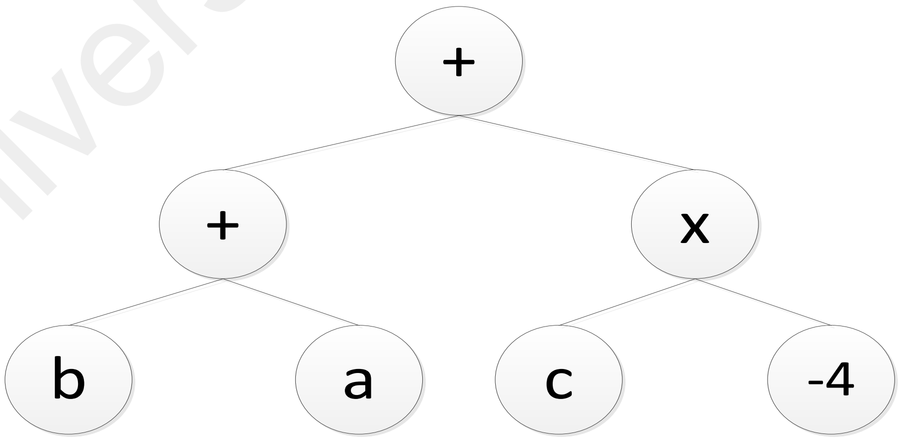


Figure 5.3: An example of ET after rotation

5.7 Adaptive Neuro Fuzzy Inference System (ANFIS)

(Jang, 1993) integrated a Fuzzy Inference System (FIS) with ANN to introduce ANFIS. The structure of ANFIS is composed of if-then rules and input output process of data in which the learning algorithm of ANN is utilized for training. ANFIS is a methodology employed to simulate complex nonlinear mappings using neural network learning and fuzzy inference methodologies (Bektas Ekici et al., 2011). It adjusts membership function and the related parameters approach towards the target data sets (Wu et al., 2009). The combined back-propagation learning algorithm and least squares method is performed together in the learning algorithm to raise the precision of ANFIS and bring the results close to the target.

ANFIS uses five layers in its structure (Admuthe et al., 2010): a fuzzified layer, product layer, normalized layer, defuzzified layer, and a total output layer. A simple structure of ANFIS including two inputs of *x* and *y*, and one output is shown in Figure 5.4 (Hadizadeh et al., 2010).

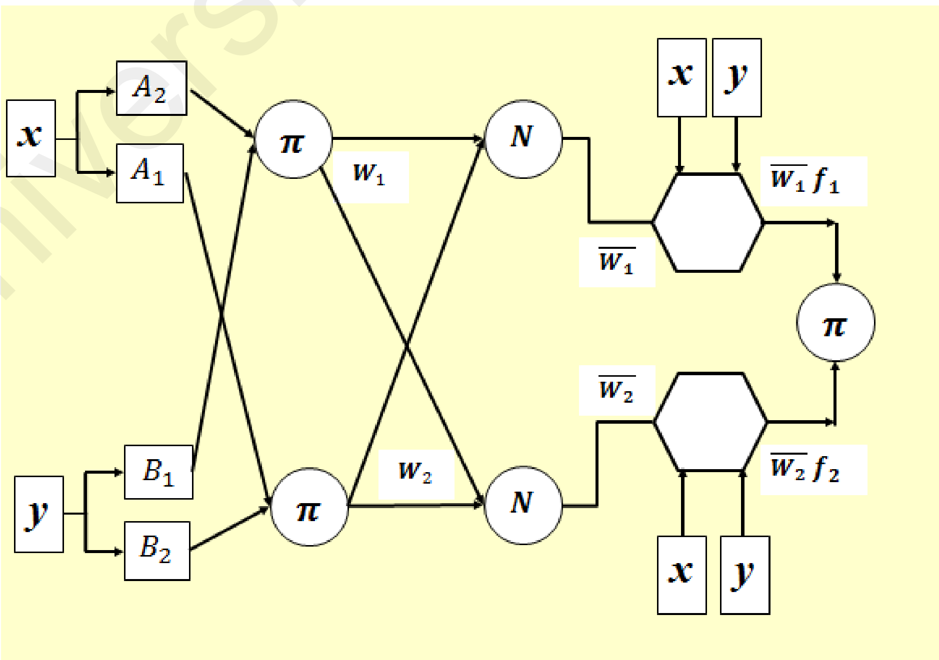


Figure 5.4: The structure of ANFIS

Layer1. Every node in this layer is an adaptive node with a node function.

$$O_{1,i} = \mu_{Ai}(x), \quad i = 1,2 \tag{5.4}$$

$$O_{1,i} = \mu_{Bi-2}(y), \quad i = 3, \tag{5.5}$$

Where x and y are assumed to be the input nodes, A and B are the linguistic labels, μ_{Ai} and μ_{Bi} are the membership functions for Ai and Bi fuzzy sets, respectively, and $O_{1,i}$ is the output of the node *i* in the first layer. In ANFIS, Bell function is usually used as a membership function.

$$\mu_A(x) = \frac{1}{1+\{\frac{x-c}{a}\}77^{2b}} \tag{5.6}$$

a, b and c are assumed as premise parameters respectively.

Layer 2. In this layer the firing strength of each rule is determined through multiplication:

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y), \qquad i = 1,2 \tag{5.7}$$

Layer 3: Every node in the third layer, as the normalized layer, computes the ratio of the *i*th rule's firing strengths to the sum of all rules' firing strengths.

In this layer the calculation of the ratio of

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2}, \qquad i = 1,2 \tag{5.8}$$

Layer 4: In this layer every node *i* is adaptive with a node function.

$$O_{4,i} = \overline{w_i}f_i = \overline{w_i}\,(p_i x + q_i y + r_i), \qquad i = 1,2 \tag{5.9}$$

Where$\overline{w_i}$is the output of layer 3 and linear p_i, q_i and r_i are referred to as consequent parameters.

Layer 5. In this layer the overall output of ANFIS is computed as the summation of all incoming signals.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad i = 1,2 \tag{5.10}$$

ANFIS applies a hybrid learning rule algorithm which uses back propagation algorithm for the parameters in Layer 1 and the least square method is utilizedfor training parameters (Ho et al., 2002).

5.8 Multi-Layer Perceptron (MLP)

MLP is a feed forward-based architecture of ANN (Cakir et al., 2014) which is usually trained with Back Propagation (BP) learning algorithm shown in Figure 5.5. There are at least three layers in an MLP network including an input layer, one hidden layer of neurons and an output layer. Each of these layers has several processing units and each unit is fully interconnected with weighted connections to units in the subsequent layer (Gandomi et al., 2011a). There are a number of nodes in each layer. Every input is multiplied by the interconnection weights of the nodes (Mirzahosseini et al., 2011). Finally, the output (h_j) is as follows:

$$h_j = f\left(\sum_i x_i w_{ij} + b\right) \tag{5.11}$$

Where f () is the activation function (e.g. Hyperbolic tangent sigmoid or log-sigmoid), x_i is the activation of *the ith node in a layer* and $w_{ij}$is the weight of the connection joining the *jth* neuron in a layer with the *ith* neuron in the previous layer, and *b* is the bias for the neuron.

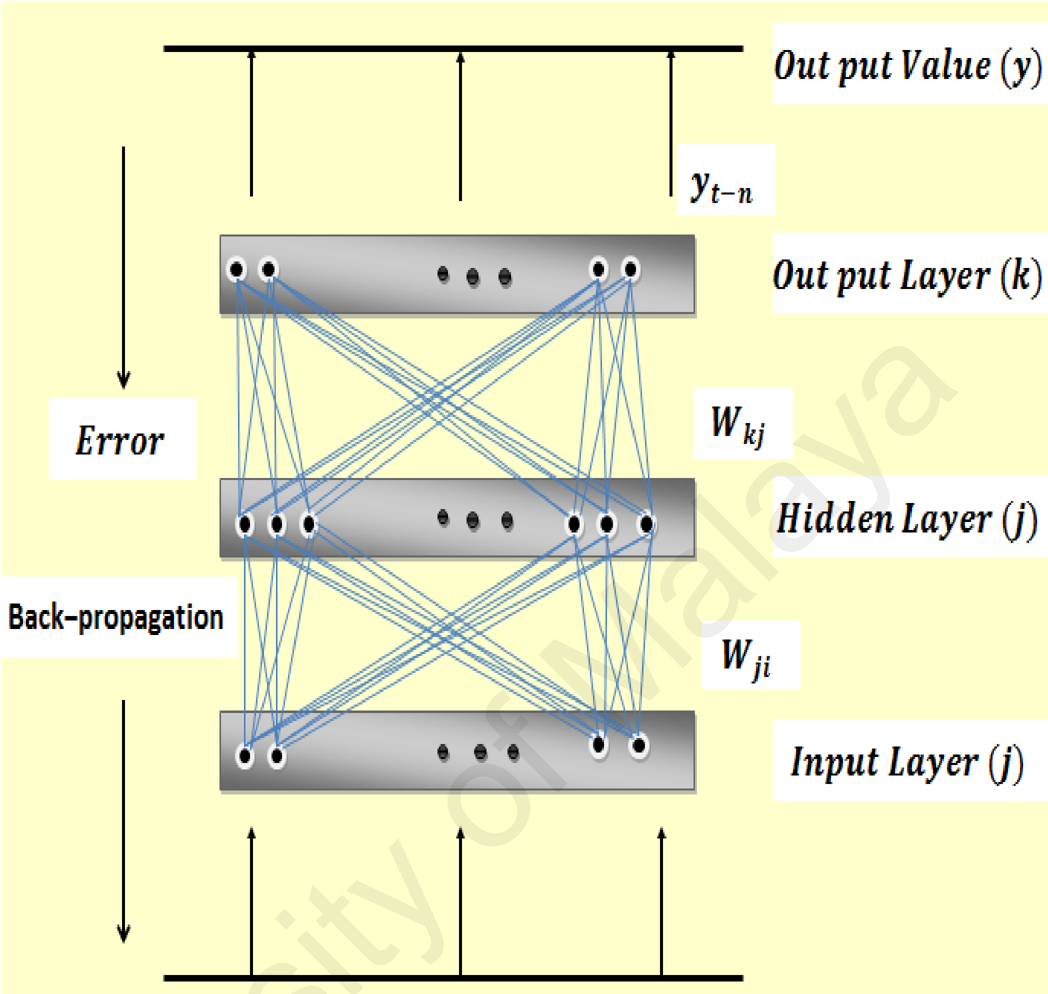


Figure 5.5: The structure of MLP neural network

5.9 TOPSIS

TOPSIS was initially developed by (Yoon et al., 1995). The main advantages of TOPSIS are as: a) it is simple, b) it uses simple mathematical equations for determining the best alternative, c) its computation processes are straight forward. The basic idea of this technique is that the best alternative should have the minimum distance to the positive ideal solution and the maximum distance from the negative ideal solution. In the first step of the method, the positive and negative ideal solutions are established. To show these numbers, the decision matrix is formed and normalized. Then, the positive ideal solution (A^{+}) is obtained by choosing the largest normalized and weighted score for each attribute. Also, the negative ideal solution (A^{-}) is calculated by choosing the least normalized and weighted score of each criterion. In the next step using the following formula the distance of each alternative from positive ideal solution and negative ideal solution are obtained.

$$d_i^* = \sum_{j=1}^{n} dv(v_{ij}, v_j^*), i = 1,2, \dots, m \quad (5.12)$$

$$d_i^- = \sum_{j=1}^{n} dv(v_{ij}, v_j^-), i = 1,2, \dots, m \quad (5.13)$$

where ${v_j}^*$is the positive ideal, ${v_j}^-$ is the negative ideal for the attributes j.

By the use of these numbers, Closeness Coefficient (CC_i) of each alternative is derived:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \quad (5.14)$$

Alternative A_i is closer to the PIS and farther from NIS as CC_i approaches to 1.

5.10 The proposed method

This study intends to introduce a new AI-based approach called GEP to solve the problems discussed above to make the sustainable supplier selection and evaluation process easier for decision makers. Indeed, the aim of this section is to extend the previous models such as (Güneri et al., 2011), (Golmohammadi, 2011), (Golmohammadi et al., 2009), and (Vahdani et al., 2012) model to deal with the supplier evaluation and selection problem. Actually through GEP, a mathematical model is provided for the suppliers' performance on the basis of sustainable criteria. The proposed model is very useful in making a strategic decision for maintaining the collaboration with the suppliers. The model is illustrated in Figure 5.6. Generally, the proposed GEP model has the following features:

1. Introduces a robust AI technique in the area of supplier selection.
2. Needs no assumption about the functional form.
3. Provides a clear mathematical model for the performance based on the determined criteria and enables managers (decision makers) to analyze the suppliers' behavior and understand how each criterion influences the efficiency.
4. Predicts the future of suppliers' behavior.

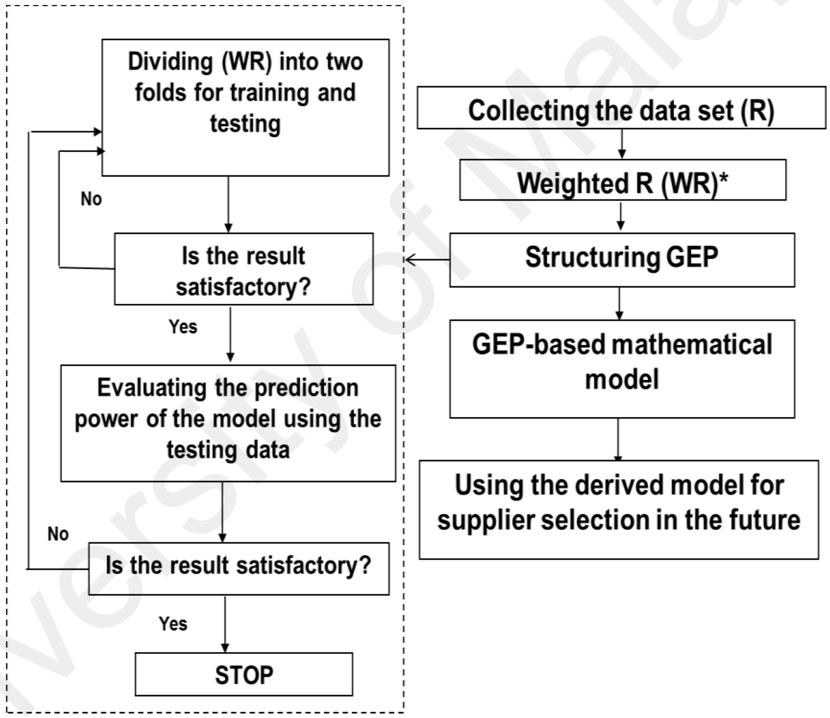


Figure 5.6: The flowchart of the proposed model

Note: the importance degree of each criterion obtained through the questionnaire is used for calculating the weight of each criterion. If ID_j shows the importance degree of criterion j then:

$$W_j = \frac{ID_j}{\sum_{j=1}^{n} ID_j} \tag{5.15}$$

Where n is the number of criteria.

As mentioned before, this study was focused to improve the previous models proposed for evaluating suppliers' performance with respect to the sustainable criteria. The steps of the model are similar to other AI-based proposed models in supplier evaluation (Golmohammadi, 2011; Golmohammadi et al., 2009; Güneri et al., 2011; Kuo et al., 2010b; Özkan et al., 2014; Vahdani et al., 2012). The steps of the model are as follows:

- Collecting data set (R): For collecting data set a questionnaire is developed and the manager of the company is asked to give us his/her opinion about the suppliers by filling in the questionnaire. This data set is called R.
- Obtaining the weighted data set for training and testing (WR): After gathering R, the weighted data set was obtained by multiplying R with the weight derived from the first objective (section 4.3) which is called WR.
- Structuring GEP-model using the training data set: After collecting the weighted data set known as (WR), it is divided into two parts for training (75%) and testing (25%). In the training, the optimized parameters of GEP are determined and consequently the most accurate mathematical GEP model is derived. And in the testing the predictive ability of the obtained model (in training) is assessed. Since there is no exact rule for finding the best structure, several runs are carried out until no significant minimization of error was observed through the run.
- Developing the GEP-based mathematical model for the performance (output) based on the criteria (inputs): After structuring by the training data set, the mathematical GEP model is obtained.
- Evaluating the predictive ability of the model using the testing data set: After finding the GEP model, the testing data set (25%) is used to show the accuracy of the model in performance estimation.

As stated earlier, despite the good performance of the previous AI-based techniques, a significant limitation of these methods is that they do not provide practical prediction equations for the performance (output) based on the criteria (inputs) (see (Golmohammadi, 2011; Golmohammadi et al., 2009; Kuo et al., 2012; Özkan et al., 2014; Vahdani et al., 2012)). Thus, it is very hard for managers (decision makers) to use and interpret these models (Mostafavi et al., 2013). But this research solve the problem of the black box by introducing GEP which generates you an explicit mathematical model for the performance based on the determined attributes.

5.11 Chapter Summary

This chapter of the research first stated the drawback of the existing predictive AI techniques in the field of supplier selection (black box). In this sub-section, those some issues still cannot be addressed were determined. In the second sub-section, the aim of the current (GEP) model was presented. The assumptions of the model were shown in the third subsection of this section. Next, the numerical scales for evaluating and collecting related data set were explained. Afterwards, the GEP approach was completely explained. In the next sub-section, a brief overview of ANFIS, as one of the most accurate neural based model, was given. In sub-section 5.8, a brief overview of ANN was described. In sub-section 5.9, the process of TOPSIS, as a ranking technique was explained. Finally, the steps of the proposed model were explained (see Figure 5.6).

CHAPTER 6: REAL CASE STUDY AND RESULTS & DISCUSSION

6.1 Introduction

According to Malaysian Investment Development Authority (MIDA), manufacturing industries in Malaysia includes Non-Metallic Mineral Industry, Aerospace, Textiles and Apparel Industry, Basic Metal Products, Food Technology and Sustainable Resources, Machinery and Equipment, Medical Devices, Petrochemical and Polymer Industry and Pharmaceuticals. The case study of this research is categorized in Basic Metal Products. Malaysia's basic metal industry consists of two main sub-industries including the iron and steel industries and the non-ferrous metal industries. It is worth noting that the selected case company is considered as a company of Iron and steel sub-industry. It should be mentioned that the iron and steel sub-industry provides an important linkage for the supply of basic raw materials and components to other sectors of the Malaysian economy, especially electrical/electronic industry, automotive industry, furniture industry, machinery industry and engineering fabrication industry.

BHS STEEL SDN. BHD Company[3] was established in 1988 in Malaysia. This company manufactures the primary processed steel products that are using in industry, like angle profile, C shaped profile, different types of I-beams etc. This firm has more than 20 employees and monthly production capacity of more than 95 tons of steel. Thirty three (33) suppliers work with this company to supply the needed raw materials for one specific item. The manager of company needs to evaluate the suppliers based on the three main aspects (economic, environmental and social) to improve the performance of the sustainability of the SCM of the company. To this end, the

[3] It should be mentioned that using a real case study is a method to prove the applicability of the developed model and also the literature shows that using one case study along with one real data set is a common way in SCM (see (Çelebi et al., 2008; Kuo et al., 2010b; Vahdani et al., 2012; Wu, 2009) (Diabat et al., 2014; Diéguez et al., 2015; Oztaysi, 2014)).

developed model is applied to assess the 33 suppliers with respect to the determined attributes. By implementing the model, the manager of the company can determine the suppliers' performance for the future. In addition, they can decide which suppliers can continue with the company and which suppliers must improve their performance. Generally, this research study helps the manager to increase the efficiency of the SCM of the company.

6.2 Implementation of the model and the Results

The first step of the proposed model, as explained, is data collection using the 1-5 scale. As mentioned in the previous section, after determining the 13 criteria and 46 sub-criteria in all the three aspects (see Figure 6.1) a questionnaire was developed and the manager of the company was asked to give us his idea about the suppliers for the first quarter of year 2015 (January, February and March) by filling in the questionnaire. Table 6.1 shows the collected data set (R) from the company. Since there are many sub-criteria and it makes the run time longer and the modeling process complicated, the average data set related to the main criteria was used. For example, Green transportation (G.Tr) consists of two sub-criteria ($c_{9.1}, c_{9,2}$), and after the manager gave his idea about the two sub-criteria, the mean value is used for the criterion of G.Tr. After gathering R, the weighted data set was obtained by multiplying R with the weight derived from the first objective (section 4.3) which is called WR. Table 6.2 shows the weighted data set.

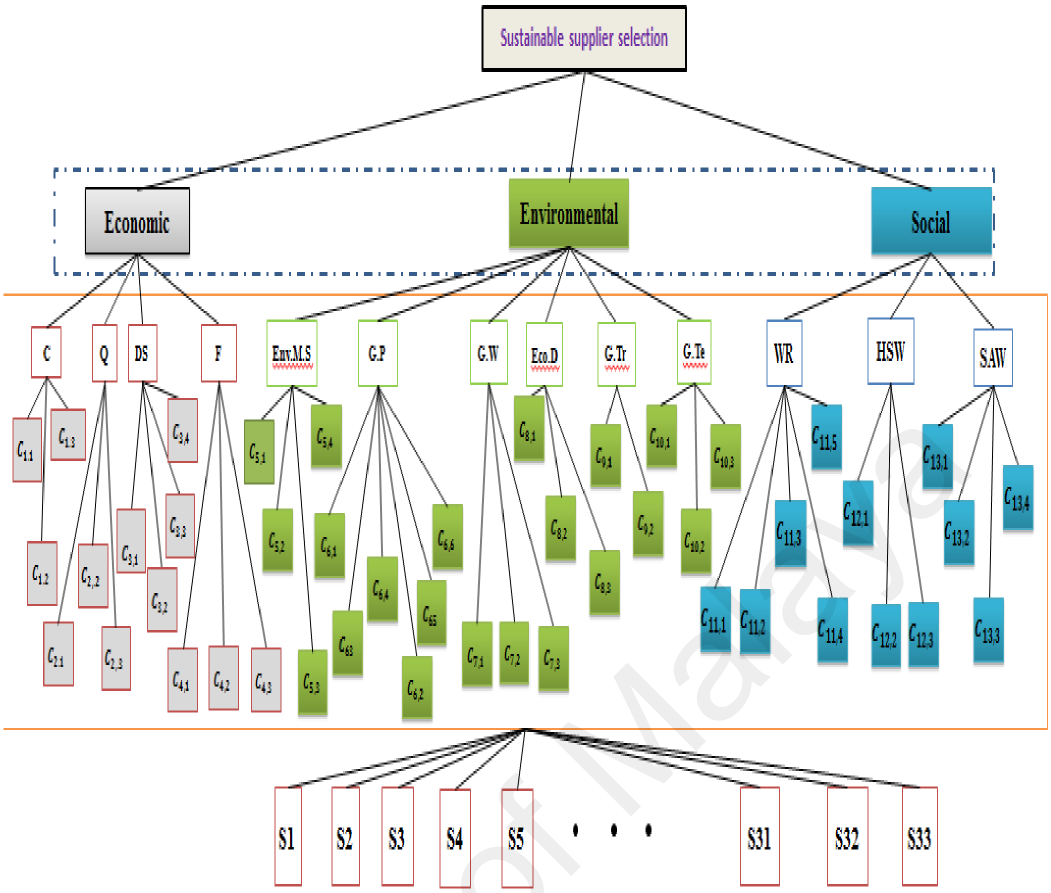


Figure 6.1: The evaluative criteria and their corresponding sub-criteria

Q: Quality; C: Cost; D: Delivery; F: Flexibility; S: Service; TC: Technical Capability; Lo: Logistic; En.P: Environmental Performance; G.Im: Green Image; G.In: Green Innovation; Env.M: Environmental Management; Po: Pollution; CSR: Corporate social responsibility; EP: Employment practices; HS: Health and safety.

Table 6.1: The data collected from January to March (the three first months of the year 2015)

S	C	Q	DS	F	Env	GP	GW	Eco	GTr	Gte	WR	HSW	SAW	Performance
S1	2	4	3	3	1	2	3	3	2	2	2	1	3	3
S2	4	4	3	2	3	3	5	4	3	3	2	3	4	4
S3	3	3	4	2	3	3	3	2	2	2	1	2	2	3
S4	4	4	5	3	3	4	3	3	4	3	4	3	2	5
S5	4	3	3	2	1	3	2	2	2	3	3	2	2	2
S6	3	5	3	5	3	4	3	3	5	4	4	3	3	6
S7	5	4	4	3	5	5	3	4	5	3	3	4	4	7
S8	2	2	1	3	3	1	2	2	2	3	2	1	3	1
S9	2	2	4	4	3	3	3	3	2	3	2	2	2	5
S10	3	1	2	2	4	3	2	3	4	2	3	2	3	4
S11	2	1	2	2	4	3	1	2	1	2	1	1	3	1
S12	3	3	2	4	3	4	5	3	4	3	3	4	2	4
S13	5	4	3	3	4	4	2	5	3	3	3	4	3	6
S14	1	2	2	4	2	2	3	2	2	3	2	1	2	1
S15	3	2	4	4	3	3	2	1	1	3	2	3	3	4
S16	5	5	3	3	4	4	3	3	4	5	3	4	3	7
S17	5	4	4	3	2	3	2	2	3	4	3	3	2	5
S18	2	5	3	5	4	2	5	2	3	3	3	4	3	5
S19	3	5	4	4	3	2	5	3	1	2	2	3	3	5
S20	4	2	2	1	3	3	1	2	1	1	2	3	1	4
S21	3	4	2	3	3	3	1	2	1	1	2	2	2	3
S22	3	3	2	3	2	2	2	2	3	2	2	1	1	3
S23	3	3	4	4	3	4	2	4	4	3	2	2	2	5
S24	4	5	5	3	3	2	3	3	4	3	3	4	5	6
S25	4	3	3	4	3	2	2	3	4	2	2	2	3	4
S26	3	5	5	5	5	4	4	4	3	3	4	5	4	7
S27	5	5	5	4	4	5	3	5	4	3	4	3	4	7
S28	1	1	2	4	4	3	3	2	1	1	3	2	3	2
S29	3	5	3	3	2	2	4	2	1	2	2	2	3	3
S30	4	3	5	5	3	5	3	2	3	2	3	2	5	6
S31	4	3	3	4	3	4	2	3	3	2	2	3	3	5
S32	4	5	5	3	3	4	3	3	2	2	2	3	3	5
S33	4	3	5	4	3	3	2	2	1	2	2	1	3	4

Table 6.2: The weighted data set

Weights	0.093	0.087	0.0855	0.0835	0.080	0.0732	0.071	0.069	0.067	0.066	0.078	0.075	0.067	
Criteria	**C**	**Q**	**DS**	**F**	**Env.**	**GP**	**GW**	**Eco.**	**GTr**	**Gte**	**WR**	**HSW**	**SAW**	**P**
S1	0.187	0.373	0.280	0.280	0.093	0.18	0.280	0.280	0.186	0.186	0.186	0.093	0.280	3
S2	0.373	0.373	0.280	0.187	0.280	0.283	0.467	0.373	0.280	0.280	0.187	0.280	0.373	4
S3	0.280	0.280	0.373	0.186	0.280	0.280	0.280	0.186	0.186	0.186	0.093	0.186	0.186	3
S4	0.373	0.373	0.467	0.280	0.280	0.373	0.280	0.280	0.373	0.280	0.373	0.280	0.186	5
S5	0.373	0.280	0.280	0.186	0.093	0.280	0.186	0.186	0.186	0.280	0.280	0.186	0.186	2
S6	0.280	0.467	0.280	0.467	0.280	0.373	0.280	0.280	0.467	0.373	0.373	0.280	0.280	6
S7	0.467	0.373	0.373	0.280	0.467	0.467	0.2803	0.373	0.467	0.280	0.280	0.373	0.373	6
S8	0.186	0.186	0.093	0.280	0.280	0.093	0.186	0.186	0.186	0.280	0.186	0.093	0.280	1
S9	0.186	0.186	0.373	0.373	0.280	0.280	0.280	0.280	0.186	0.280	0.186	0.186	0.186	2
S10	0.280	0.093	0.186	0.186	0.373	0.280	0.186	0.280	0.373	0.186	0.280	0.186	0.280	2
S11	0.186	0.093	0.186	0.186	0.373	0.280	0.093	0.186	0.093	0.186	0.093	0.093	0.280	1
S12	0.280	0.280	0.186	0.373	0.280	0.373	0.467	0.280	0.373	0.280	0.280	0.373	0.186	4
S13	0.467	0.373	0.280	0.280	0.373	0.373	0.186	0.467	0.280	0.280	0.280	0.373	0.280	6
S14	0.093	0.186	0.186	0.373	0.186	0.186	0.280	0.186	0.186	0.280	0.186	0.093	0.186	1
S15	0.280	0.186	0.373	0.373	0.280	0.280	0.186	0.093	0.093	0.280	0.186	0.280	0.280	2
S16	0.467	0.467	0.280	0.280	0.373	0.373	0.280	0.280	0.373	0.467	0.280	0.373	0.280	6
S17	0.467	0.373	0.373	0.280	0.186	0.280	0.186	0.186	0.280	0.373	0.280	0.280	0.186	5
S18	0.186	0.467	0.280	0.467	0.373	0.186	0.467	0.186	0.280	0.280	0.280	0.373	0.280	5
S19	0.280	0.467	0.373	0.373	0.280	0.186	0.467	0.280	0.093	0.186	0.186	0.280	0.280	5
S20	0.373	0.186	0.186	0.093	0.280	0.280	0.093	0.186	0.093	0.093	0.186	0.280	0.093	3
S21	0.2803	0.373	0.186	0.280	0.280	0.280	0.093	0.186	0.093	0.093	0.186	0.186	0.186	3
S22	0.280	0.280	0.186	0.280	0.186	0.186	0.186	0.186	0.280	0.186	0.186	0.093	0.093	3
S23	0.2803	0.280	0.373	0.373	0.280	0.373	0.186	0.373	0.373	0.280	0.186	0.186	0.186	4
S24	0.373	0.467	0.467	0.280	0.280	0.186	0.280	0.280	0.373	0.280	0.280	0.373	0.467	6
S25	0.373	0.280	0.280	0.373	0.280	0.186	0.186	0.280	0.373	0.186	0.186	0.186	0.280	4
S26	0.280	0.467	0.467	0.467	0.467	0.373	0.373	0.373	0.280	0.280	0.373	0.467	0.373	6
S27	0.467	0.467	0.467	0.373	0.373	0.467	0.280	0.46	0.373	0.280	0.373	0.288	0.373	7
S28	0.093	0.093	0.186	0.373	0.373	0.280	0.280	0.186	0.093	0.093	0.280	0.186	0.280	2
S29	0.2803	0.467	0.2803	0.280	0.186	0.186	0.373	0.186	0.093	0.186	0.186	0.186	0.280	3
S30	0.373	0.280	0.467	0.467	0.280	0.467	0.2803	0.186	0.280	0.186	0.280	0.186	0.467	4
S31	0.373	0.280	0.280	0.373	0.280	0.373	0.186	0.280	0.280	0.186	0.186	0.280	0.280	4
S32	0.373	0.467	0.467	0.280	0.280	0.373	0.280	0.280	0.186	0.186	0.186	0.280	0.280	5
S33	0.373	0.280	0.467	0.373	0.280	0.280	0.186	0.186	0.093	0.186	0.186	0.093	0.280	4

According to Figure 5.5, after collecting the weighted data set known as (WR), it is divided into two parts for training (75%) and testing (25%). Thus, of the 33 data set 25 were taken for the training process and the remaining 8 data sets (25%) were used for the testing purpose (see Figure 6.2). In the training, the optimized parameters of GEP are determined and consequently the most accurate mathematical GEP model is derived. Several runs are carried out until no significant minimization of error was observed through the run. Table 6.3 shows the optimized parameters of GEP for finding the most precise model. The number of programs in the population is set by the population size (number of chromosomes). Increasing the number of the chromosomes increases the program run time. The suitable number of population depends on the number of possible solutions and complexity of the problem. Number of gene and head size are the two most important parts of structure of chromosome which have an impact on the complexity of the model. Each gene is coded for a different sub-expression tree or sub-ET.

Table 6.3: The optimized parameters for the GEP algorithm

	Parameters	Value
General	Chromosomes	30
	Function set	×,/,+,-, power (x, y*)
	Number of genes	8
	Head size	12
	Linking function	Addition
Fitness Function	MSE	
Genetic Operators	Mutation rate	0.044
	One- point recombination rate	0.2
	Two- point recombination rate	0.3
	Gene recombination rate	0.1
	Gene transportation rate	0.1
Numerical Constant	Constants per gene	2
	Data type	Floating Point
	Lower bound	-10
	Upper bound	+10
Number of runs	163	

In this survey, 163 different runs were done to find the best mathematical model in terms of R-value and MSE. Equation 6.1 shows the final decision model which can be used by the managers of the company for strategic decisions making in long term. In training the GEP model, R square and MSE were 0.879 and 0.839, respectively, while for testing these values were 0.942 and 0.208. Figure 6.2 (a) and (b) shows the accuracy of the GEP model in training and testing. In this study, GenXpro Tools 4.00 was used to run the GEP model. (The picture of each part of the GenXproTools 4.00 including data importing, settings, results and model is given in Appendix E).

$$\boldsymbol{P}=\left(x_9 \times \left(x_5 - \frac{x_7+\frac{x_4}{7.71}}{x_1}\right)\right) + x_4 + \left(x_{10} + \left((x_8 - x_9) \times x_{13}\right)\right) +$$

$$(8.16x_2 \times x_8) + x_2 + x_3 + x_{11} + x_8 + \left(x_{12} \times \left(x_6 + (x_8)^2 + x_2\right)\right) +$$

$$2x_5 + \left[\left(\frac{x_9 \times x_4}{(1-x_1)\times x_8}\right) \times x_{11}\right] + x_1 - \left(\frac{\left(x_{10} - \left[x_{10} \times \left(x_{10} \times \left(\frac{x_1}{x_3} - 0.73\right)\right)\right]\right)}{x_2}\right) +$$

$$\left[\left(x_6 \times \left(\frac{x_3 + x_5 - x_9}{x_5}\right)\right) + x_2\right] \tag{6.1}$$

$x_1 = Cost\ (C),$

$x_2 = Delivery\ \&\ Service\ (DS),$

$x_3 = Eco - Design\ (Eco),$

$x_4 = Env.M.S,$

$x_5 = Flexibility\ (F),\ x_6 = Green\ Production\ (GP),$

$x_7 = Green\ Technology\ (GTe),$

$x_8 = Green\ Transportation\ (GTr),$

$x_9 = \boldsymbol{Green\ Warehousing(GW)},$

$x_{10} = \boldsymbol{Health\ and\ Safety\ at\ Work\ (HSW)},$

$x_{11} = \boldsymbol{Quality\ (Q)},$

$x_{12} = \boldsymbol{Supportive\ Activities\ (SA)},$

$x_{13} = \boldsymbol{Workers'Rights\ \ (WR)}$

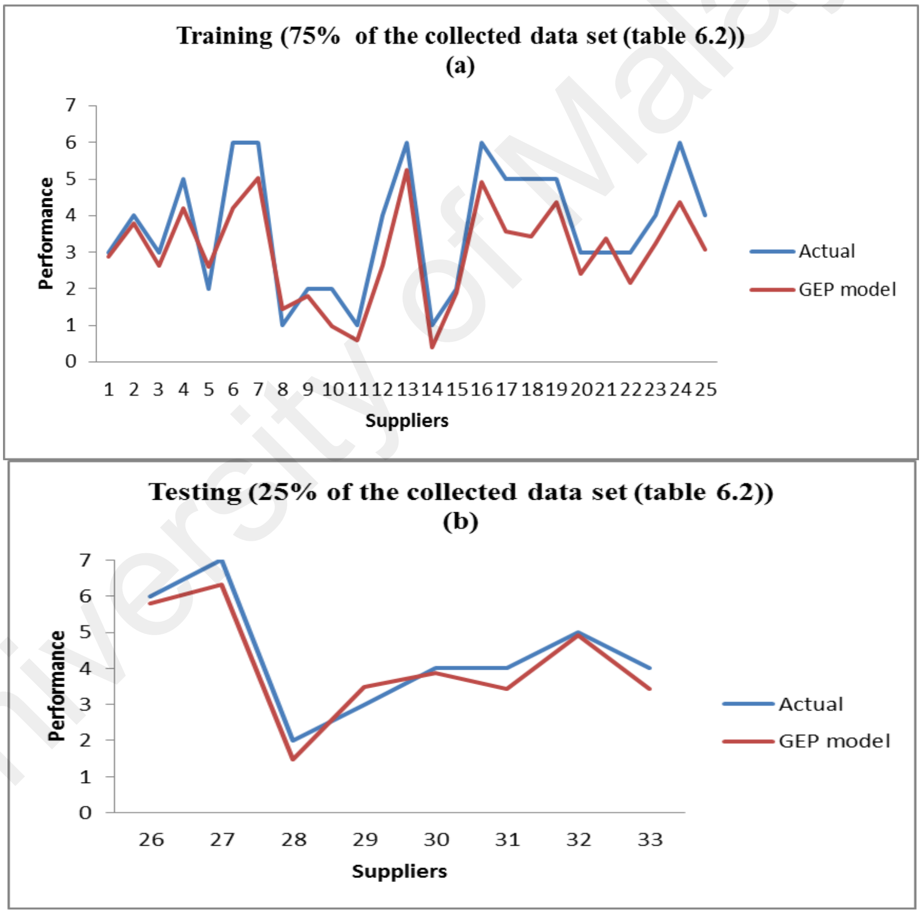


Figure 6.2: The training and testing of the GEP model for performance evaluation

As it is observed from figure 6.2 (a), the generated mathematical GEP model is very close to the reality. That is, the model could recognize the pattern of the suppliers' performance based on the determined criteria very well. In addition, figure 6.2 (b) proves that the developed GEP model is accurate to predict those supplier which their related data set have not been used in training (testing data set). It means, this model is a robust model for estimating the supplier performance.

The MATLAB code[4] of the derived GEP model is as given

```
function result = gepModel(d)
G1C0 = -7.713257;
G1C1 = -7.629028;
G2C0 = 6.639679;
G2C1 = 8.164489;
G3C0 = -4.026489;
G3C1 = -0.555176;
G4C0 = 1.173248;
G4C1 = -3.656891;
G5C0 = -5.304321;
G5C1 = -2.347504;
G6C0 = -7.152374;
G6C1 = 9.165191;
G7C0 = -0.73761;
G7C1 = 3.418762;
G8C0 = 6.639679;
G8C1 = 8.164489;
varTemp = 0.0;
varTemp = ((d[5](9)*(d(5)-((d(7)-(d(4)/G1C0))/d(1))))+d(4));
varTemp = varTemp + (((d(10)+((d(8)-d(9))*d(13)))+(d(2)*(d(8)*G2C1)))+(d(2)+d(3)));
varTemp = varTemp + (d(11)+d(8));
varTemp = varTemp + (d(12)*((d(6)+(d(8)*d(8)))+d(2)));
varTemp = varTemp + d(5);
varTemp = varTemp + (d(5)+((d(9)/((((d(9)/d(9))-d(1))*d(8))/d(4)))*d(11)));
varTemp = varTemp + (d(1)-((d(10)-(d(10)*(d(10)*((d(1)/d(3))+G7C1))))/d(2)));
varTemp = varTemp + ((G8C0+((d(6)*(((d(3)+d(5))-d(9))/d(5)))-G8C0))+d(2));
result[6] = varTemp;
```

The results show that supplier 27 is the best supplier. It is followed by S7, S10 and S17, respectively. Also, the three weakest suppliers are S29, S25 and S13, respectively. To show the applicability of the model for new data sets, a new data set related to the second quarter of year 2015 was collected. Note that in this time the manager was not asked to give his opinion about the performance of the alternatives, he was only asked to give a number ranging from 1-5 for the sub-criteria and using the

[4] Note that there is no difference between the MATLAB codes generated by the GenXpro Tools4 and the equation 6.1. As explained in appendix E, the software can present the model as different programming languages. In this study the MATLAB was selected for showing the programming codes.

[5] d shows the input variable. In the MATLAB codes d (1) means x_1(Cost (C)), d (2) means x_2(Delivery & Service (DS)) to d (13) means x_{13}(Workers' Rights (WR)) in equation 6.1.

[6] Results (varTemp) is the output (performance).

generated GEP model the performance and ranking were computed. Table 6.4 shows the collected the data set.

Table 6.4: The data set related to the second quarter of 2015

S	C	Q	DS	F	Env.	GP	GW	Eco.	GTr	GTe	WR	HSW	SAW
S1	4	3	3	4	3	4	2	3	3	2	2	3	3
S2	4	5	5	3	3	4	3	3	2	2	2	3	3
S3	4	3	5	4	3	3	2	2	1	2	2	1	3
S4	4	2	2	1	3	3	1	2	1	1	2	3	1
S5	3	4	2	3	3	3	1	2	1	1	2	2	2
S6	3	3	2	3	2	2	2	2	3	2	2	1	1
S7	5	4	4	3	5	5	3	4	5	3	3	4	4
S8	2	2	1	3	3	1	2	2	2	3	2	1	3
S9	2	2	4	4	3	3	3	3	2	3	2	2	2
S10	4	3	3	2	1	3	2	2	2	3	3	2	2
S11	3	5	3	5	3	4	3	3	5	4	4	3	3
S12	3	1	2	2	4	3	2	3	4	2	3	2	3
S13	2	1	2	2	4	3	1	2	1	2	1	1	3
S14	3	3	4	4	3	4	2	4	4	3	2	2	2
S15	4	5	5	3	3	2	3	3	4	3	3	4	5
S16	4	3	3	4	3	2	2	3	4	2	2	2	3
S17	3	5	5	5	5	4	4	4	3	3	4	5	4
S18	2	5	3	5	4	2	5	2	3	3	3	4	3
S19	3	5	4	4	3	2	5	3	1	2	2	3	3
S20	3	3	2	4	3	4	5	3	4	3	3	4	2
S21	5	4	3	3	4	4	2	5	3	3	3	4	3
S22	1	2	2	4	2	2	3	2	2	3	2	1	2
S23	2	4	3	3	1	2	3	3	2	2	2	1	3
S24	4	4	3	2	3	3	5	4	3	3	2	3	4
S25	3	3	4	2	3	3	3	2	2	2	1	2	2
S26	4	4	5	3	3	4	3	3	4	3	4	3	2
S27	5	5	5	4	4	5	3	5	4	3	4	3	4
S28	1	1	2	4	4	3	3	2	1	1	3	2	3
S29	3	5	3	3	2	2	4	2	1	2	2	2	3
S30	4	3	5	5	3	5	3	2	3	2	3	2	5
S31	3	2	4	4	3	3	2	1	1	3	2	3	3
S32	5	5	3	3	4	4	3	3	4	5	3	4	3
S33	5	4	4	3	2	3	2	2	3	4	3	3	2

By comparing Table 6.4 with 6.1 it can be seen that there is no big difference between the manager's opinion for evaluating the suppliers in the three first month of year 2015 and in the second three month of year 2015. Table 6.5 shows the weighted data set. As mentioned in section 5.10, by multiplying Table 6.4 (original data set (R)) with the weight (derived from the first objective) the weighted data set (WR) is obtained.

Table 6.5: The weighted data set related to the second three months of year 2015 (April, May and June)

	C	Q	DS	F	Env.	GP	GW	Eco.	GTr	Gte	WR	HSW	SAW
S1	0.372	0.261	0.255	0.332	0.24	0.292	0.142	0.207	0.204	0.132	0.156	0.2265	0.201
S2	0.372	0.435	0.425	0.249	0.24	0.292	0.213	0.207	0.136	0.132	0.156	0.2265	0.201
S3	0.372	0.261	0.425	0.332	0.24	0.219	0.142	0.138	0.068	0.132	0.156	0.0755	0.201
S4	0.372	0.174	0.17	0.083	0.24	0.219	0.071	0.138	0.068	0.066	0.156	0.2265	0.067
S5	0.279	0.348	0.17	0.249	0.24	0.219	0.071	0.138	0.068	0.066	0.156	0.151	0.134
S6	0.279	0.261	0.17	0.249	0.16	0.146	0.142	0.138	0.204	0.132	0.156	0.0755	0.067
S7	0.465	0.348	0.34	0.249	0.4	0.365	0.213	0.276	0.34	0.198	0.234	0.302	0.268
S8	0.186	0.174	0.085	0.249	0.24	0.073	0.142	0.138	0.136	0.198	0.156	0.0755	0.201
S9	0.186	0.174	0.34	0.332	0.24	0.219	0.213	0.207	0.136	0.198	0.156	0.151	0.134
S10	0.372	0.261	0.255	0.166	0.08	0.219	0.142	0.138	0.136	0.198	0.234	0.151	0.134
S11	0.279	0.435	0.255	0.415	0.24	0.292	0.213	0.207	0.34	0.264	0.312	0.2265	0.201
S12	0.279	0.087	0.17	0.166	0.32	0.219	0.142	0.207	0.272	0.132	0.234	0.151	0.201
S13	0.186	0.087	0.17	0.166	0.32	0.219	0.071	0.138	0.068	0.132	0.078	0.0755	0.201
S14	0.279	0.261	0.34	0.332	0.24	0.292	0.142	0.276	0.272	0.198	0.156	0.151	0.134
S15	0.372	0.435	0.425	0.249	0.24	0.146	0.213	0.207	0.272	0.198	0.234	0.302	0.335
S16	0.372	0.261	0.255	0.332	0.24	0.146	0.142	0.207	0.272	0.132	0.156	0.151	0.201
S17	0.279	0.435	0.425	0.415	0.4	0.292	0.284	0.276	0.204	0.198	0.312	0.3775	0.268
S18	0.186	0.435	0.255	0.415	0.32	0.146	0.355	0.138	0.204	0.198	0.234	0.302	0.201
S19	0.279	0.435	0.34	0.332	0.24	0.146	0.355	0.207	0.068	0.132	0.156	0.2265	0.201
S20	0.279	0.261	0.17	0.332	0.24	0.292	0.355	0.207	0.272	0.198	0.234	0.302	0.134
S21	0.465	0.348	0.255	0.249	0.32	0.292	0.142	0.345	0.204	0.198	0.234	0.302	0.201
S22	0.093	0.174	0.17	0.332	0.16	0.146	0.213	0.138	0.136	0.198	0.156	0.0755	0.134
S23	0.186	0.348	0.255	0.249	0.08	0.146	0.213	0.207	0.136	0.132	0.156	0.0755	0.201
S24	0.372	0.348	0.255	0.166	0.24	0.219	0.355	0.276	0.204	0.198	0.156	0.2265	0.268
S25	0.279	0.261	0.34	0.166	0.24	0.219	0.213	0.138	0.136	0.132	0.078	0.151	0.134
S26	0.372	0.348	0.425	0.249	0.24	0.292	0.213	0.207	0.272	0.198	0.312	0.2265	0.134
S27	0.465	0.435	0.425	0.332	0.32	0.365	0.213	0.345	0.272	0.198	0.312	0.2265	0.268
S28	0.093	0.087	0.17	0.332	0.32	0.219	0.213	0.138	0.068	0.066	0.234	0.151	0.201
S29	0.279	0.435	0.255	0.249	0.16	0.146	0.284	0.138	0.068	0.132	0.156	0.151	0.201
S30	0.372	0.261	0.425	0.415	0.24	0.365	0.213	0.138	0.204	0.132	0.234	0.151	0.335
S31	0.279	0.174	0.34	0.332	0.24	0.219	0.142	0.069	0.068	0.198	0.156	0.2265	0.201
S32	0.465	0.435	0.255	0.249	0.32	0.292	0.213	0.207	0.272	0.33	0.234	0.302	0.201
S33	0.465	0.348	0.34	0.249	0.16	0.219	0.142	0.138	0.204	0.264	0.234	0.2265	0.134

After obtaining WR for the second quarter of year 2015, the values related to the criteria were replaced in equation 6.1 for obtaining the performance values of the suppliers as well as ranking. Table 6.6 shows that supplier 27 is the best supplier followed by suppliers 17 and 21 respectively. In addition, S13 is the weakest supplier. In comparison with the results derived from the first quarter of year 2015, it can be seen that still supplier 27 is the best supplier with the highest performance and supplier 13 is the weakest supplier with the lowest performance.

Table 6.6: The suppliers' performance and ranking based on the second collected data set

Performance	Supplier	Ranking
5.246	s27	1
4.836	s17	2
4.265	s21	3
4.221	s7	4
4.143	s2	5
4.082	s32	6
3.741	s15	7
3.655	s11	8
3.654	s19	9
3.645	s26	10
3.423	s30	11
3.199	s24	12
3.113	s33	13
3.101	s18	14
2.981	s29	15
2.975	s3	16
2.958	s1	17
2.875	s5	18
2.85	s14	19
2.667	s16	20
2.53	s23	21
2.399	s20	22
2.34	s25	23
2.322	s10	24
2.087	s4	25
1.942	s6	26
1.782	s31	27
1.73	s9	28
1.405	s28	29
1.256	s8	30
1.001	s12	31
0.678	s22	32
0.66	s13	33

6.3 Chapter Summary

This section began with introducing the real case study (the Malaysian company). Then, the steps of the proposed model described in the previous section were implemented for this case company. In the first step, the manager was asked to measure the suppliers' performance and the determined criteria (Table 6.1) for the first quarter of year 2015 based on the thirteen main criteria in the three aspects (see Figure 6.1). The collected data set was multiplied with their weight (Table 6.2). 75% of the data set (Table 6.2) was dedicated for training. In the training, the GEP was obtained (see equation 6.1). The remaining the data set (25%) was used to show the prediction accuracy of the developed GEP model. Figure 6.2 illustrates the accuracy of the GEP model in training and testing in terms of R square and MSE. To prove the applicability of the model, the data set related to the second quarter of year 2015 was collected (see Tables 6.4, 6.5 and 6.6). This data set was replaced in equation 6.1 and the suppliers' performance were calculated and ranked (see Table 6.6).

CHAPTER 7: VERIFYING THE VALIDITY OF THE PROPOSED INTELLIGENT MODEL

7.1 Introduction

In this section, the derived model using GEP is evaluated based on statistical methods and comparing with the previous predictive AI techniques. Moreover, the ranking determined by the GEP model is compared with the ranking obtained by TOPSIS (as one of the most common techniques in ranking).

7.2 Validation of the model using statistical methods

To evaluate the performance of the GEP model (equation 6.1), (Smith, 1986) recommended the following attributes:

I. If a model gives $|R| > 0.8$, a strong correlation exists between the predicted and real values.

II. If a model gives $0.2 < |R| < 0.8$ a correlation exists between the predicted and real values.

III. If a model gives $|R| < 0.2$, a weak correlation exists between the predicted and real values.

In all conditions, the error values (e.g. MSE) should be at the minimum (Mostafavi et al., 2013). The results show that the GEP model provides very precise predictions both for the training (R = 0.937, MSE = 0.839) and testing (R = 0.970, MSE = 0.208) data sets. In addition, new factors suggested by (Golbraikh et al., 2002) were checked for external validation of the models on the validation data sets. It is recommended that at least one slope of the regression lines (k or k') through the origin should be close to 1 (Mollahasani et al., 2011). It should be noted that k and k' are the slopes of the regression lines between the regressions of actual output (h_i) against predicted output (t_i) or t_i against h_i through the origin, i.e. h_i=$k\ t_i$ and $t_i = k'h_i$, respectively. In addition, the performance indexes of m and n should be less than 0.1 (*m and n* are the two factors for evaluating the model performance). Recently, Roy and Roy, (2008) presented a confirmed indicator (R_m) of the external predictability of models. For $R_m > 0.5$, the condition is satisfied. Either the squared correlation coefficient (through the origin) between predicted and experimental values (${R_o}^2$), or the squared correlation coefficient between experimental and predicted values (${R_{o'}}^2$) should be close to R^2 and to 1 (Alavi et al., 2011a; Mostafavi et al., 2013; Mostafavi et al., 2014). The considered validation criteria and the relevant results obtained by the models are given in Table 7.1.

In item one R should be greater than 0.8, and in the developed model R is 0.970 (0.17 more than the standard condition). In the second item k should be between 0.85 and 1.15. For the developed model the k value is 1.05 which means the condition has been satisfied. In the third item, k' should be between 0.85 and 1.15. The result shows that the k' value for the GEP model is in this range (0.957). According to items 4 and 5, m and n values should be smaller than 0.1. These values for m and n in the developed model are 0.098 and 0.046, respectively. Finally R_m should be greater than 0.5. For this item, R_m value of the developed model is 0.61 (0.11 more than the standard condition). As shown, the developed model satisfies all the requisite conditions. The validation phase ensures that the proposed model is strongly suitable and applicable.

Table 7.1: Statistical factors of the decision model for external validation

Item	**Formula**	**Condition**	**Testing**
1	R	$0.8 < R$	0.970
2	$k = \frac{\sum_{i=1}^{n}(h_i \times t_i)}{{h_i}^2}$	$0.85 < k < 1.15$	1.05
3	$k' = \frac{\sum_{i=1}^{n}(h_i \times t_i)}{{t_i}^2}$	$0.85 < k' < 1.15$	0.957
4	$m = \frac{R^2 - {R_o}^2}{R^2}$	$m < 0.1$	0.098
5	$n = \frac{R^2 - {R_o'}^2}{R^2}$	$n < 0.1$	0.046
6	$R_m = R^2 \times \left(1 - \sqrt{\lvert R^2 - {R_o}^2 \rvert}\right)$	$0.5 < R_m$	0.610
Where	${R_o}^2 = 1 - \frac{\sum_{i=1}^{n}(t_i - {h_i}^o)^2}{\sum_{i=1}^{n}(t_i - \bar{t_i})^2}, {h_i}^o = k \times t_i$		
	${R_o'}^2 = 1 - \frac{\sum_{i=1}^{n}(h_i - {t_i}^o)^2}{\sum_{i=1}^{n}(h_i - \bar{h_i})^2}, {t_i}^o = k' \times h_i$		

7.3 Comparison with other AI-based techniques

In order to have an idea about predictive ability of the GEP–based model, we compare the results derived from the proposed model with the results from the other AI-based models such as ANFIS and MLP-ANN as the two useful predictive techniques[7]. The ANFIS model uses Sugeno-type for training. In the ANFIS, each criterion as an each input includes two Gaussian membership functions. Therefore, there are different rules in the developed ANFIS structure. Note that the Gaussian membership functions were selected between the membership functions for the lowest MSE result. Thus, the ANFIS model was built with a hybrid learning algorithm and trained for 1000 epochs. Table 7.2 shows the important parameters involved in the ANFIS training algorithm.

[7] Generally, it must be noted that there is no exact rule to find the best structure in intelligent-based models. Consequently, the design is a trial and error process and may affect the precision of the resulting trained AI model. Therefore, in order to find the optimized structure for training the ANFIS and MLP-ANN models, several runs were done with different structures.

Table 7.2: The parameters of ANFIS for training

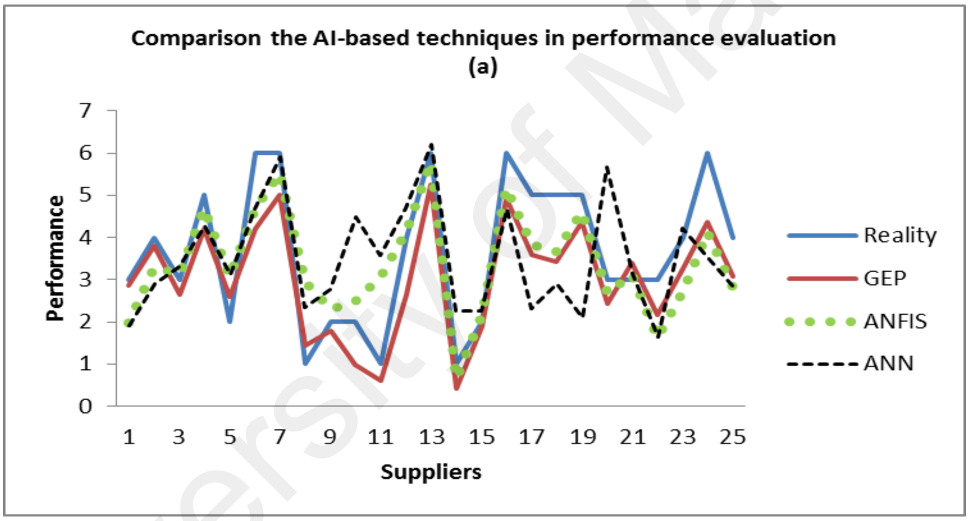
Parameters	Setting
Epoch	1000
Generate FIS	Grid partition
Error Tolerance	0
Optimum method	Hybrid
MF type for inputs	Trimf
MF type for output	Linear
Number of MF to each input	3

Addition to ANFIS, MLP neural network as one of the other famous AI-technique widely used in behavioral modeling is applied in this research to be compared with the GEP model. Table 7.3 shows the structure of the MLP model using the training data set (the same data set used for training GEP). In this paper, Neuro Solution 5 was used to run the ANN model.

Table 7.3: The parameters of MLP neural network for training

Parameters	Setting
Epoch	1000
Learning method	Momentum
Rate of the learning method	0.7
Number of hidden layers	2
Number of nodes (first layer / second layer)	4/4
Motivation function (first layer)	Sin(x)
Motivation function (second layer)	Tan(x)

Figure 7.1 (a, and b) compares the accuracy of the three AI-based models in both training and testing. In training, R square and MSE for ANFIS are 0.668 and 1.037, respectively while these values for ANN are 0.411 and 2.469 respectively. In addition, R square and MSE in testing for ANFIS and ANN are 0.818, 0.638 and 0.639, 0.896, respectively. In addition, it can be seen that the accuracy of the GEP model is more than the two traditional AI techniques in terms of R square and MSE. It is worth mentioning again that ANFIS and ANN only propose a neural-based structure, they are unable to provide an explicit mathematical model and the decision makers have to run the structures again for the new data sets if they need to use new data sets.



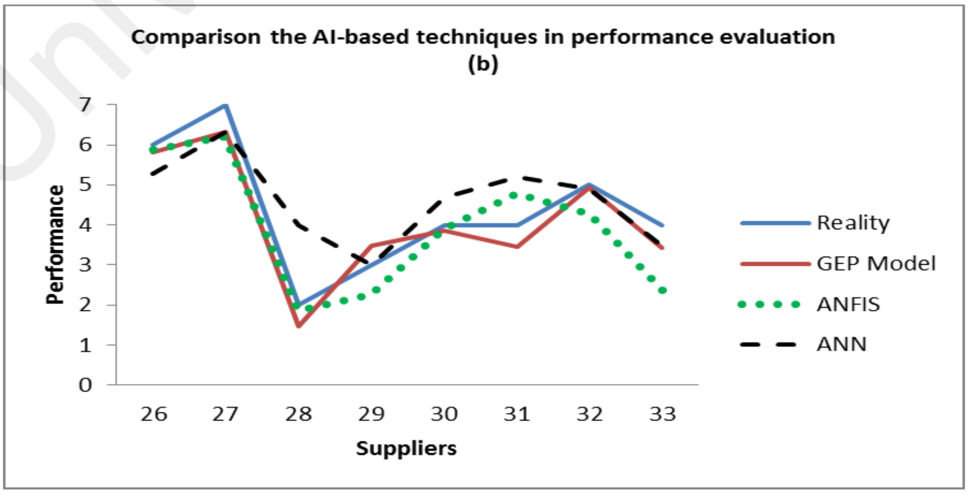


Figure 7.1: Accuracy of the GEP model in comparison with the two other AI models in estimating the performance.

Figure 7.1 (a) shows that the most accurate model in training is the GEP model (Because it has the closest distance to the reality). After GEP, ANFIS is the best neural-based model in training. In addition, Figure 7.1(b) shows that both GEP and ANFIS are accurate in testing process. Generally, in both training and testing ANN was the weakest model for performance evaluation.

7.4 Comparison with other MCDM-based Ranking Method (TOPSIS)

To show the ability of the model in ranking, TOPSIS as an accurate technique in prioritizing was used so that its results are compared with the derived results by the GEP[8] model. To this end, a new data set was collected related to the second quarter of year 2015. The steps of TOPSIS are as:

Step 1: collecting data set. In order to rank the suppliers using TOPSIS, data related to the second quarter of 2015 (Table 6.4) was used.

[8] Note that to calculate the suppliers' performance, the data of Table6.4 was replaced in equation 6.1 (see Table 6.6).

Step 2: Normalizing the dataset.

Table 7.4: The normalized data set

C	Q	DS	F	Env.	GP	GW	Eco.	GTr	GTe	WR	HSW	SAW
0.8	0.6	0.6	0.8	0.6	0.8	0.4	0.6	0.6	0.4	0.5	0.6	0.6
0.8	1	1	0.6	0.6	0.8	0.6	0.6	0.4	0.4	0.5	0.6	0.6
0.8	0.6	1	0.8	0.6	0.6	0.4	0.4	0.2	0.4	0.5	0.2	0.6
0.8	0.4	0.4	0.2	0.6	0.6	0.2	0.4	0.2	0.2	0.5	0.6	0.2
0.6	0.8	0.4	0.6	0.6	0.6	0.2	0.4	0.2	0.2	0.5	0.4	0.4
0.6	0.6	0.4	0.6	0.4	0.4	0.4	0.4	0.6	0.4	0.5	0.2	0.2
1	0.8	0.8	0.6	1	1	0.6	0.8	1	0.6	0.8	0.8	0.8
0.4	0.4	0.2	0.6	0.6	0.2	0.4	0.4	0.4	0.6	0.5	0.2	0.6
0.4	0.4	0.8	0.8	0.6	0.6	0.6	0.6	0.4	0.6	0.5	0.4	0.4
0.8	0.6	0.6	0.4	0.2	0.6	0.4	0.4	0.4	0.6	0.8	0.4	0.4
0.6	1	0.6	1	0.6	0.8	0.6	0.6	1	0.8	1	0.6	0.6
0.6	0.2	0.4	0.4	0.8	0.6	0.4	0.6	0.8	0.4	0.8	0.4	0.6
0.4	0.2	0.4	0.4	0.8	0.6	0.2	0.4	0.2	0.4	0.3	0.2	0.6
0.6	0.6	0.8	0.8	0.6	0.8	0.4	0.8	0.8	0.6	0.5	0.4	0.4
0.8	1	1	0.6	0.6	0.4	0.6	0.6	0.8	0.6	0.8	0.8	1
0.8	0.6	0.6	0.8	0.6	0.4	0.4	0.6	0.8	0.4	0.5	0.4	0.6
0.6	1	1	1	1	0.8	0.8	0.8	0.6	0.6	1	1	0.8
0.4	1	0.6	1	0.8	0.4	1	0.4	0.6	0.6	0.8	0.8	0.6
0.6	1	0.8	0.8	0.6	0.4	1	0.6	0.2	0.4	0.5	0.6	0.6
0.6	0.6	0.4	0.8	0.6	0.8	1	0.6	0.8	0.6	0.8	0.8	0.4
1	0.8	0.6	0.6	0.8	0.8	0.4	1	0.6	0.6	0.8	0.8	0.6
0.2	0.4	0.4	0.8	0.4	0.4	0.6	0.4	0.4	0.6	0.5	0.2	0.4
0.4	0.8	0.6	0.6	0.2	0.4	0.6	0.6	0.4	0.4	0.5	0.2	0.6
0.8	0.8	0.6	0.4	0.6	0.6	1	0.8	0.6	0.6	0.5	0.6	0.8
0.6	0.6	0.8	0.4	0.6	0.6	0.6	0.4	0.4	0.4	0.3	0.4	0.4
0.8	0.8	1	0.6	0.6	0.8	0.6	0.6	0.8	0.6	1	0.6	0.4
1	1	1	0.8	0.8	1	0.6	1	0.8	0.6	1	0.6	0.8
0.2	0.2	0.4	0.8	0.8	0.6	0.6	0.4	0.2	0.2	0.8	0.4	0.6
0.6	1	0.6	0.6	0.4	0.4	0.8	0.4	0.2	0.4	0.5	0.4	0.6
0.8	0.6	1	1	0.6	1	0.6	0.4	0.6	0.4	0.8	0.4	1
0.6	0.4	0.8	0.8	0.6	0.6	0.4	0.2	0.2	0.6	0.5	0.6	0.6
1	1	0.6	0.6	0.8	0.8	0.6	0.6	0.8	1	0.8	0.8	0.6
1	0.8	0.8	0.6	0.4	0.6	0.4	0.4	0.6	0.8	0.8	0.6	0.4

Step 3: Calculating the weighted normalized data set (see equation 5.15 for calculating the weight). Note that the weights have been calculated and used in Table 6.2 (the first row of Table 6.2). Table 7.5 shows the result of this step.

Table 7.5: The weighted normalized data set

C	Q	DS	F	Env.	GP	GW	Eco.	GTr	GTe	WR	HSW	SAW
0.074	0.052	0.051	0.067	0.048	0.059	0.028	0.041	0.040	0.026	0.039	0.045	0.040
0.074	0.087	0.086	0.050	0.048	0.059	0.043	0.041	0.027	0.026	0.039	0.045	0.040
0.074	0.052	0.086	0.067	0.048	0.044	0.028	0.028	0.013	0.026	0.039	0.015	0.040
0.074	0.035	0.034	0.017	0.048	0.044	0.014	0.028	0.013	0.013	0.039	0.045	0.013
0.056	0.070	0.034	0.050	0.048	0.044	0.014	0.028	0.013	0.013	0.039	0.030	0.027
0.056	0.052	0.034	0.050	0.032	0.029	0.028	0.028	0.040	0.026	0.039	0.015	0.013
0.093	0.070	0.068	0.050	0.080	0.073	0.043	0.055	0.067	0.040	0.059	0.060	0.054
0.037	0.035	0.017	0.050	0.048	0.015	0.028	0.028	0.027	0.040	0.039	0.015	0.040
0.037	0.035	0.068	0.067	0.048	0.044	0.043	0.041	0.027	0.040	0.039	0.030	0.027
0.074	0.052	0.051	0.033	0.016	0.044	0.028	0.028	0.027	0.040	0.059	0.030	0.027
0.056	0.087	0.051	0.084	0.048	0.059	0.043	0.041	0.067	0.053	0.078	0.045	0.040
0.056	0.017	0.034	0.033	0.064	0.044	0.028	0.041	0.054	0.026	0.059	0.030	0.040
0.037	0.017	0.034	0.033	0.064	0.044	0.014	0.028	0.013	0.026	0.020	0.015	0.040
0.056	0.052	0.068	0.067	0.048	0.059	0.028	0.055	0.054	0.040	0.039	0.030	0.027
0.074	0.087	0.086	0.050	0.048	0.029	0.043	0.041	0.054	0.040	0.059	0.060	0.067
0.074	0.052	0.051	0.067	0.048	0.029	0.028	0.041	0.054	0.026	0.039	0.030	0.040
0.056	0.087	0.086	0.084	0.080	0.059	0.057	0.055	0.040	0.040	0.078	0.075	0.054
0.037	0.087	0.051	0.084	0.064	0.029	0.071	0.028	0.040	0.040	0.059	0.060	0.040
0.056	0.087	0.068	0.067	0.048	0.029	0.071	0.041	0.013	0.026	0.039	0.045	0.040
0.056	0.052	0.034	0.067	0.048	0.059	0.071	0.041	0.054	0.040	0.059	0.060	0.027
0.093	0.070	0.051	0.050	0.064	0.059	0.028	0.069	0.040	0.040	0.059	0.060	0.040
0.019	0.035	0.034	0.067	0.032	0.029	0.043	0.028	0.027	0.040	0.039	0.015	0.027
0.037	0.070	0.051	0.050	0.016	0.029	0.043	0.041	0.027	0.026	0.039	0.015	0.040
0.074	0.070	0.051	0.033	0.048	0.044	0.071	0.055	0.040	0.040	0.039	0.045	0.054
0.056	0.052	0.068	0.033	0.048	0.044	0.043	0.028	0.027	0.026	0.020	0.030	0.027
0.074	0.070	0.086	0.050	0.048	0.059	0.043	0.041	0.054	0.040	0.078	0.045	0.027
0.093	0.087	0.086	0.067	0.064	0.073	0.043	0.069	0.054	0.040	0.078	0.045	0.054
0.019	0.017	0.034	0.067	0.064	0.044	0.043	0.028	0.013	0.013	0.059	0.030	0.040
0.056	0.087	0.051	0.050	0.032	0.029	0.057	0.028	0.013	0.026	0.039	0.030	0.040
0.074	0.052	0.086	0.084	0.048	0.073	0.043	0.028	0.040	0.026	0.059	0.030	0.067
0.056	0.035	0.068	0.067	0.048	0.044	0.028	0.014	0.013	0.040	0.039	0.045	0.040
0.093	0.087	0.051	0.050	0.064	0.059	0.043	0.041	0.054	0.066	0.059	0.060	0.040
0.093	0.070	0.068	0.050	0.032	0.044	0.028	0.028	0.040	0.053	0.059	0.045	0.027
0.093	0.087	0.086	0.084	0.080	0.073	0.071	0.069	0.067	0.066	0.078	0.075	0.067
0.019	0.017	0.017	0.017	0.016	0.015	0.014	0.014	0.013	0.013	0.020	0.015	0.013

Step 4: Calculating the positive ideal solution (d^{+}) and negative ideal solution (d^{-}) and calculating the closeness coefficient CC_i (see Table 7.6).

Table 7.6: The results of step 4

d^+	d^-	CC_i
0.029714	0.014987	0.335278
0.027518	0.020689	0.429168
0.038197	0.015557	0.28941
0.052193	0.007514	0.125845
0.046121	0.008594	0.157064
0.047137	0.006613	0.123027
0.014882	0.031039	0.675919
0.04974	0.005436	0.098526
0.03593	0.010944	0.233474
0.040866	0.010552	0.205219
0.019272	0.026175	0.575953
0.038129	0.010845	0.22145
0.054621	0.005177	0.08658
0.028825	0.015826	0.354439
0.020926	0.025432	0.548602
0.033018	0.013699	0.293243
0.013401	0.034915	0.722629
0.025348	0.022247	0.467428
0.030723	0.018703	0.378411
0.024616	0.018473	0.428719
0.02161	0.024098	0.527218
0.048281	0.006087	0.111954
0.043038	0.008735	0.168712
0.024943	0.018517	0.426067
0.041029	0.009123	0.181913
0.022519	0.023592	0.511631
0.013613	0.035987	0.725544
0.046113	0.00956	0.171711
0.038813	0.012625	0.245436
0.02445	0.024824	0.503792
0.038138	0.011709	0.234899
0.018194	0.027463	0.601509
0.007468	0.019071	0.718602

After finishing the calculation of TOPSIS and comparing the ranking results of the GEP model with the ranking results of TOPSIS, it is observed that there are seven suppliers with the same ranking in both methods (see Table 7.7). Green color shows the same ranking.

Table 7.7: the ranking results of the GEP model and TOPSIS as well as their similarity in ranking

TOPSIS	GEP
s27	s27
s17	s17
s33	s21
s7	s7
s32	s2
s11	s32
s15	s15
s21	s11
s26	s19
s30	s26
s18	s30
s2	s24
s20	s33
s24	s18
s19	s29
s14	s3
s1	s1
s16	s5
s3	s14
s29	s16
s31	s23
s9	s20
s12	s25
s10	s10
s25	s4
s28	s6
s23	s31
s5	s9
s4	s28
s6	s8
s22	s12
s8	s22
s13	s13

As can be see seven suppliers have the same ranking (s27, s17, 7, s15, s1, s10 and s13). Also it can be said that there are three same suppliers among top five (see Figure 7.2) and there are eight same suppliers among top ten (see figure 7.3). Therefore, it can be concluded that the GEP model is accurate in ranking.

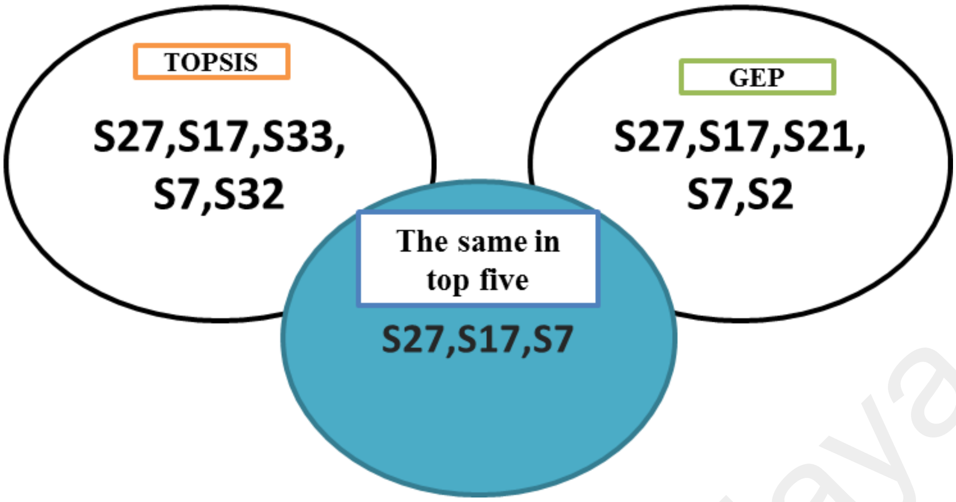


Figure 7.2: The same suppliers among top five suppliers in terms of ranking

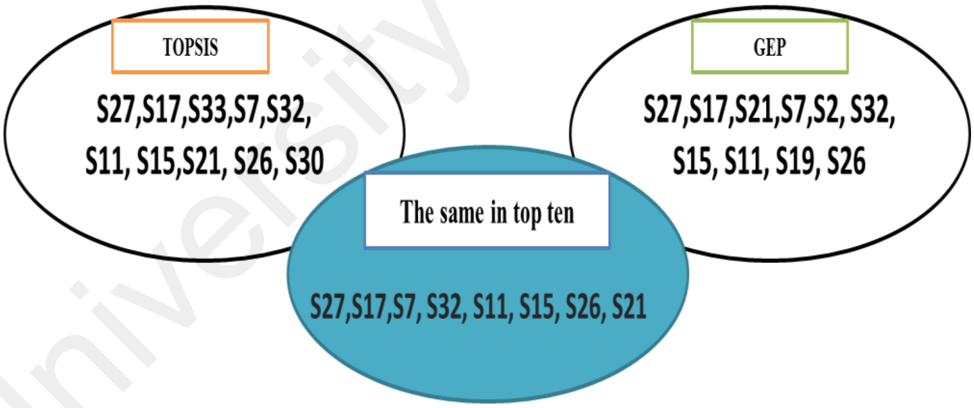


Figure 7.3: the same suppliers among top ten suppliers in terms of ranking

7.5 Chapter summary

In this section, the validity of the developed GEP-based model was verified using different ways. To show the robustness of the model, three established statistical tests (Smith, 1988; Golbraikh and Tropsha, 2002; Roy and Roy, 2008) were applied. The results showed that all the statistical conditions were satisfied by the model. In order to show the prediction power of the model, the obtained results from the GEP model was compared with those results derived from ANFIS and ANN (as the two most widely used intelligent-based techniques in performance prediction) for the testing data set. Figure 7.1 illustrates that the GEP model is the most accurate model in comparison with others. In addition, it can be stated that ANFIS is good in performance estimation, but it is not as accurate as the GEP model. Also, it is seen that the ANN model is the weakest in performance estimation. Addition to these two methods, the GEP results were compared with TOPSIS (as one of the most popular method in ranking) results to show the ranking power of the GEP model. It can be observed that the GEP model is even reliable in ranking (see Figures 7.2 and 7.3).

CHAPTER 8: CONCLUSION AND FUTUR RESEARCH

8.1 Introduction

The gaps of the research, objectives, and research methodology for solving the problems of sustainable supplier selection have been filled in the previous chapters. This chapter includes summary of the work, conclusion, future works and the limitation of the study.

8.2 Summary of the work

All the defined objectives of this research study have been achieved. This research includes three objectives. The first objective is to develop a comprehensive list of criteria and sub-criteria for suppliers' performance sustainability assessment as well as measuring their importance and applicability. A set consisting of 13 main criteria and 46 sub-criteria were determined and their importance and applicability were measured using a questionnaire-based survey. Through this survey the first objective was achieved. The findings of the first objective, which can be found in Chapter 4, show that economic criteria are the most effective criteria for sustainability performance evaluation. It is followed by environmental criteria and social criteria. Among the economic-based criteria, quality is the most important attribute. It is followed by cost and delivery and service (DS). Furthermore, Cronach's alpha and Mann–Whitney U-test were applied to show the validity of the collected data set in the first objective.

As stated in the previous chapters, although the predictive AI techniques like ANFIS, ANN, SVM, etc. have been successfully applied for supplier selection, they are considered as black box system, which means they cannot provide an explicit mathematical model for the performance according to the criteria. The second objective is to develop an intelligent model for overcoming the shortcoming of the previous AI techniques in performance evaluation and ranking. In order to solve this major problem, GEP as one of the newest evolutionary algorithms was applied. Therefore, by prospering the GEP-based model, the second objective was also achieved. Findings from the second objective, which can be found in Chapters 5 and 6, show that GEP can really solve the problem of black box and simulate the suppliers' performance as an explicit mathematical model.

The third objective is to investigate the performance of the proposed model using the different methods (please see chapter 7). By conducting different statistical methods and comparing the derived result from the proposed model with the other existing AI and MCDM models, the robustness of the proposed model was demonstrated in terms of performance estimation and ranking power. Findings of the third objective show that the GEP-based model is more accurate than other intelligent-based models (ANFIS and ANN). In addition, the ranking result of the GEP model in comparison with TOPSIS represented that this model is reliable in ranking. At the end, it is worth mentioning that after implementing the model and evaluating the suppliers of the Malaysian company based on the sustainability criteria, the manager of the company accepted the results of the study as a true evaluation tool.

8.3 Conclusion

Appropriate suppliers directly improve the SCM performance. Therefore, many managers have concentrated on this issue to increase the efficiency of the supply chain of their companies. This study conducted a research in the field of sustainable supplier selection to help the managers for facing the problems in this area. The main conclusions of this study are as below:

1. A comprehensive list of criteria and sub-criteria for evaluating sustainability of suppliers' performance as well as establishing their importance and applicability in the real world has been developed.
2. A new intelligent approach known as GEP has been introduced to the literature of supplier selection.
3. A GEP-based model was proposed with respect to the determined criteria for performance evaluation and ranking.
4. The presented GEP model can be applied for those companies having problems in selecting appropriate suppliers for long-term cooperation.

The study expanded the general knowledge of decision making and supplier selection and came up with the publications of ISI and conference papers (Appendix F shows the first page of each paper).

8.4 Future works

There are several opportunities to extend this research in the future. The first objective of this research focused on sustainability criteria for evaluation of suppliers' performance. Adding the carbon management criteria and their corresponding sub-criteria to this list could be worthy for the future work.

Another room for future research that would be of interest is using fuzzy numbers for collecting data set. Sustainable supplier selection comprises ambiguity and fuzziness in a real life. Thus, fuzzy numbers are very useful to deal with imprecision and vagueness for data collection in a real life case study. In addition, using newer AI-based techniques such as Multi Expression Programming (MEP), Simulated Annealing-Genetic Programming (SA-GP) and comparing their results with this study can be considered new idea for developing the GEP model.

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LIST OF PUBLICATIONS AND PAPERS PRESENTED

1. **Fallahpour, A**., Olugu, E., Musa, S., Khezrimotlagh, D., & Wong, K. (2015). An integrated model for green supplier selection under fuzzy environment: application of data envelopment analysis and genetic programming approach. *Neural Computing and Applications*, 1-19. doi: 10.1007/s00521-015-1890-3

Abstract:

Green supplier selection has been identified as one of the most effective ways of achieving Green Supply Chain Management (GSCM). Data Envelopment analysis is one of the common approaches in performance evaluation. Charnes, Cooper and Rhodes (CCR) and Banker, Charnes and Cooper (BCC) are the two best-known models of Data Envelopment Analysis (DEA) to have been used widely in supplier evaluation and selection. However both CCR and BCC are neither able to discriminate between technically efficient DMUs nor can they simultaneously consider both input and output orientations. In addition, it has been demonstrated that DEA needs advanced computers when large dataset is used. Artificial Neural Network (ANN) as an intelligent approach was introduced to solve the problem of DEA in terms of huge dataset (time consuming and computational complexity). On the other hand, ANN is a black box system (lacking of an explicit mathematical model). In this paper, the Kourosh & Arash Method (KAM) as a robust model of DEA was integrated with a new genetic-based intelligent approach namely Genetic Programming (GP) to overcome the aforementioned drawbacks of both (BCC/CCR) DEA and ANN in supplier selection. Indeed, in this paper, GP provides a robust non-linear mathematical equation for the suppliers' efficiency using the determined criteria. That is to say, the GP-based model, not only overcomes the black box system, but also decreases the time consuming of the efficiency calculation. In addition, the managers can use the derived GP model for assessing the suppliers'

performance in the next years. To validate the model, Adaptive Neuro Fuzzy Inference System (ANFIS) as a powerful tool was used to compare the result with GP-based model. In addition, parametric analysis and unseen data set were used to validate the precision of the model.

Key words: Green supplier selection, Data Envelopment Analysis (DEA), Artificial Intelligence, Genetic Programming (GP), parametric analysis

2) **Fallahpour, A.**, Olugu, E. U., & Musa, S. N. A hybrid model for supplier selection: integration of AHP and multi expression programming (MEP). *Neural Computing and Applications*, 1-6. doi: 10.1007/s00521-015-2078-6

Abstract:

Supplier evaluation and selection is a complicated process which deals with conflicting attributes such as quality, cost. To mitigate the computational complexity, intelligent-based techniques have gained much popularity. But the main shortcoming of the existing models in this regard is to be a black box system. In this paper, we aim to combine analytical hierarchy process with multi-expression programming to both introduce a new evolutionary approach in the field of supplier evaluation and selection and cope with the earlier problem. To show the validity of the model, statistical test was carried out. The finding showed that the proposed model is accurate and acceptable for using in the evaluation process.

Conference Proceeding

Fallahpour, A., OLUGU, E. U., MUSA, S. N., Khezrimotlagh, D., & Singh, S. (2014). Supplier selection under fuzzy environment: A hybrid model using KAM in DEA. *Recent Developments in Data Envelopment Analysis and its Applications, 342.*

Revised paper

Alireza Fallahpour, Ezutah Udoncy Olugu, Siti Nurmaya Musa, Kuan Yew Wong; ***Integration of fuzzy AHP and fuzzy preference programming (FPP) with fuzzy TOPSIS for sustainable supplier selection;*** *Computer and Industrial Engineering* (ISI cited)

Under review papers

Alireza Fallahpour, Ezutah Udoncy Olugu, Siti Nurmaya Musa, Kuan Yew Wong; ***A predictive integrated genetic-based model for supplier evaluation and selection***; Computers and industrial engineering.(ISI Cited)

Alireza Fallahpour, Ezutah Udoncy Olugu, Siti Nurmaya Musa, Kuan Yew Wong **; A non-linear model for suppliers' performance evaluation; International journal of fuzzy systems (ISI cited).**

APPENDIX A: THE QUESTIONNAIRE FOR MEASURING IMPORTANCE AND APPLICABILITY OF THE DETERMINED CRITERIA AND SUB-CRITERIA

UNIVERSITY OF MALAYA

The Leader in Research & Innovation

QUESTIONNAIRE ON THE IMPORTANCE & APPLICABILITY OF SUSTAINABLE SUPPLIER SELECTION CRITERIA IN MALAYSIAN INDUSTRIES

Overview:

This survey forms part of a research process to enhance supply chain's performance throughout selecting the right suppliers. The primary aim of this survey is to investigate the importance and applicability of supplier selection criteria in manufacturing industries. The results and contributions are solely for the purpose of academic research and no attempt shall be made at identifying the individuals and/or the organizations they represent in any publication. Your co-operation is highly appreciated.

SECTION I: BACKGROUND INFORMATION

In this section, we would like to know you and your organisation in general

1. Name of company (**optional**) ____

2. Your Position____

3. Company's current annual sales revenue (please tick)

   Between RM 300,000 and less than US$ 15 million. ☐

   Between RM 15 million and US$ 50 million. ☐

   More than US$ 50 million. ☐

4. Sources of your raw material are coming from which region? (Please tick, you may tick more than one)

   Local ☐ Asia ☐ Middle East ☐ Oceania ☐

   Africa ☐ Europe ☐ The Americas ☐

5. Total number of employees (please tick)

   5 – 75 employees ☐ 75 – 200 employees ☐ 201 employees and above ☐

6. Does your organisation have any of the ISO 9000 certification?

   Yes ☐ please specify_________________ No ☐

7. Does your organisation have any of the ISO 14000 certification?

Yes ☐ please specify___________________ No ☐

8. Does your organisation have any of the ISO 26000 certification?

Yes ☐ please specify___________________ No ☐

9. Does your organisation have any of the ISO 3166 certification?

Yes ☐ please specify___________________ No ☐

10. Which of the following environmental excellence awards have your organisation received? (Kindly tick as many as applicable)

☐ President/Chancellor/Prime minister's environmental excellence award: e.g.________________

☐ Environmental Management excellence award: e.g.__________________

☐ State environmental award: e.g.___________________

☐ Others (Please specify) _______________

☐ None

SECTION II: IMPORTANCE & APPLICABILITY OF MEASURES FOR SUSTAINABLE SUPPLIER SELECTION

In this section, we are trying to determine the ***importance*** and ***applicability*** level of our proposed measures for selecting and evaluating suppliers. For each of the measures below, kindly circle the most appropriate number based on the following scales:

(1) **Importance Level:** Degree of how significant is the measure in selecting your suppliers:

i. 0**-** No idea, 1- not important, 2- less important, 3- important, 4- very important, 5- Extremely important.

ii.

(2) **Applicability level:** Degree of applicability of the measure:

0- No idea, 1- not applicable, 2- less applicable, 3- fairly applicable, 4- very applicable, 5- Extremely applicable.

SECTION II: IMPORTANCE & APPLICABILITY OF MEASURES FOR SUSTAINABLE SUPPLIER SELECTION

In this section, we are trying to determine the ***importance*** and ***applicability*** level of our proposed measures for selecting and evaluating suppliers. For each of the measures below, kindly circle the most appropriate number based on the following scales:

(3) **Importance Level:** Degree of how significant is the measure in selecting your suppliers:

0- No idea, 1- not important, 2- less important, 3- important, 4- very important, 5- Extremely important.

(4) **Applicability level:** Degree of applicability of the measure:

1- No idea, 1- not applicable, 2- less applicable, 3- fairly applicable, 4- very applicable, 5- Extremely applicable.

Measures / Metrics	Importance level	Applicability level
Cost • Material cost • Freight cost • After sales service cost	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)
Quality • Rejection Rate of the Product • Capability of Handling Abnormal Quality • Process for Internal Audit quality of Material	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (1) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)
Delivery & Service • Rate of Delivery • After Sales Service • Time to Solve the Complaint • On-Time Delivery	(0)(1) (2) (3) (4) (5) (0)(1) (2) (3) (4) (5) (0)(1) (2) (3) (4) (5) (0)(1) (2) (3) (4) (5)	(0)(1) (2) (3) (4) (5) (0)(1) (2) (3) (4) (5) (0)(1) (2) (3) (4) (5) (0)(1) (2) (3) (4) (5)
FLEXIBILITY • Flexibility in Giving Discount • Flexibility of Delivering Time • Flexibility in Ordering	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4)(5)
Env.M.S • ISO-14001 certification • Environmental Performance Evaluation • Eco-Labeling • Environment-Friendly Raw Materials	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)
Organizational Management • Carbon governance • Carbon policy • Carbon reduction targets	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (1) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)

Measures / Metrics	Importance level	Applicability level
Green product • Green certification • Reuse • Green Packaging • Air Emissions • Waste Water • Hazardous Wastes	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)
Green warehousing • Inventory of Hazardous Substances • Inventory of Substitute Material • Warehouse Management	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)
Process management • Energy efficiency • Measures of mitigation of carbon • Training-related carbon management • Risk assessment for low carbon requirement	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(1) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)
R&D management • Carbon accounting and Inventory • Carbon verification • Capability of low carbon design	(1) (1) (2) (3) (4) (5) (1) (1) (2) (3) (4) (5) (1) (1) (2) (3) (4) (5)	(1) (1) (2) (3) (4) (5) (1) (1) (2) (3) (4) (5) (1) (1) (2) (3) (4) (5)
Green Transportation • Green Transportation • Green Fuels	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)
Green Technology • Green raw material • Capability of R&D • Ability to alter process and product for reducing the impact on natural resources	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5) (0) (1) (2) (3) (4) (5)

Measures / Metrics	Importance level	Applicability level
Workers' Rights		
• Workers' contract	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Employment insurance	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• employment compensation	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Standard working hours	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• The right to sue the employer	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Diversity	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• flexible working	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• job opportunities	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• career development	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
Health and Safety at Work	(0) (1) (2) (3) (4) (5)	(0)(1) (2) (3) (4) (5)
• Health and safety incidents	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Training for safety at work	(0) (1) (2) (3) (4) (5)	(0)(1) (2) (3) (4) (5)
• Providing appropriate equipment at work	(0) (1) (2) (3) (4) (5)	(0)(1) (2) (3) (4) (5)
	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Disciplinary and security practices	(0) (1) (2) (3) (4) (5)	(0)(1) (2) (3) (4) (5)
Supportive Activities		
• Discrimination	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Growth at work	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Wages	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Attention to religious and cultural issues at work	(0) (1) (2) (3) (4) (5)	(0) (1) (2) (3) (4) (5)
• Workers education	(0)(1) (2) (3) (4) (5)	(0)(1) (2) (3) (4) (5)
• public services	(0)(1) (2) (3) (4) (5)	(0)(1) (2) (3) (4) (5)

APPENDIX B: THE INFORMATION OF THE RESPONDENTS

	Name of the company	Position
1	Nima Asdallahi; Renault, Iran	Logistics executive
2	Dr.Javadian; Mazandaran University of Science and Technology (MUST)	Associated professor
3	Dr.Alavi; Michigan State University, USA	Assistant professor
4	Vahid Ahmadi; PARS KHODRO (Automotive factory, Iran)	Production management
5	Dr.Amin Mahmudian; flinders university, Australia	lecturer and production management (previously)
6	Morteza Yazdani; Universidad Europea de Madrid, Spain	Production management and senior researcher
7	Dr.Moghassem; Izlamic Azad University, Iran	Consultant and associated professor
8	Dr.Barari; Virgina tech university; USA	Senior researcher
9	Mirjalol Azizov; PETRONAS Carigali SDN BHD, Malaysia	Sourcing executive
10	Moradi; Carpet industry,; Iran	Production management
11	Ali Norouzi; Material Company, Iran	Management
12	Fatemeh Shayeghi; PETRONAS, Malaysia	Senior legal officer
13	Dr.Mostafavi; Lasing Community College, USA	Lecturer
14	Dr.Mirsadeghi, Soltan Ghabus University, Oman	Post-doc researcher
15	Shahram Geraili; Food industry; Iran	Production management
16	Mohsen Mousavi; Researcher, Malaysia	Researcher
17	Dr.Zabihi; tecnalia research & innovation; Spain	Senior researcher and Associated professor at IAU
18	Elisa taghavi; Abzar gostar	Management
19	Dr.Singh; Bsaitm Faridabad, India	Associate professor
20	Dr.Mirzaii; NUS, Singapore	Senior researcher
21	Mehdi Ranjbar-Bourani; Michigan Institute of Technology (MIT), USA	Researcher
22	Dr.Peiman Valipour	Consultant and associated professor
23	Dr. Mosapour, Iran	Quality control supervisor

APPENDIX C: THE INFORMATION OF THE PANEL FOR CONTENT VALIDATION

Name: **Mirjalol Azizov**

Company: **PETRONAS Carigali SDN BHD (Malaysia)**

Position: Sourcing Executive

Group Procurement, International Exploration & Production.

Background:

Mirjalol has been with PETRONAS Carigali Uzbekistan from January 2010 till June 2013. He has joined PETRONAS Carigali Sdn Bhd since July 2012 and throughout his carrier he has been directly involved in all supply chain management, vendor selection, tender preparation and bid evaluation matters.

Name: **ZahraBatoul Mosapour**

Company: **Almahdi Aluminium (Iran)**

Position: Quality Control Supervisor

Background:

She has been with Almahdi Aluminium from 2000 till 2010. She has been in charge of vendor selection by evaluating the quality of the vendor's products based on environmental considerations such as toxicity factors, eco-labeling and ISO Standards.

Name: **Dr. Abdulrasool Moghassem**

Company: **Khazar Ris (Iran)**

POSITION: Consultant & Associated Professor – Islamic Azad University (IRAN)

Background:

He has been with textile industry 2000 till present. Amongst other things he has been in charge of supply chain management in relation to spinning, weaving, knitting and selection of suitable manufacturers based on quality of products and advancement of the technology.

Name: **Fatemeh Shayeghi**

POSITION: **Senior legal officer, group legal PETRONAS (Malaysia)**.

Background:

She has been with Petrolaim Nasional Bhd since 2013. As a member of bid evaluation committee, she has been in charge of selection of the qualified bidders in relation to PETRONAS' international procurement within south-east Asian countries namely Myanmar and Vietnam. She has been directly in charge of tender evaluation and contract administration based on the sub-contractors performance.

Name: **Moein Azadikhah**

Company: **Sirjan Teb (Iran)**

POSITION: Manager (supplier).

Background:

He has been with medical equipment industry since 2005 till present. As a supplier, he has been directly involved in observing governmental regulations in relation to environmental and social issues.

Name: **Morteza Yazdani**

POSITION: Researcher in operation research and supply chain management fields (**Spain**).

Background:

He has been with dairy industry since 2008 to 2014. He has conducted several researches in supply chain management field and published various papers in operation research. His researches have been cited 336.

Name: **Dr.Peiman Valipour**

POSITION: Associated professor in Islamic Azad University and technical consultant in various textile companies (**Iran**).

Background:

He has been working with institution of standard of Iran since 1997 till present. He has been directly involved in drafting textile standards and by taking into consideration the environmental impact.

Name: **Ronald G.H. Tan**

POSITION: The management of the BHS STEEL SDN.BHD (the case company) in Malaysia.

APPENDIX D: THE COMMENTS GIVEN BY SOME OF EXPERTS FOR THE CONTENT VALIDATION

The comments given by the experts:

Fatemeh Shayeghi: including the workers’ contract, the right to sue the employer and attention to religious and cultural issues at work to the list of the attributes of the social aspect.

ZahraBatoul Mosapour: including eco-Labeling and green certification to the list of the attributes of the environmental aspect and adding training for safety at work and providing appropriate equipment at work to the list of the attributes of the social aspect.

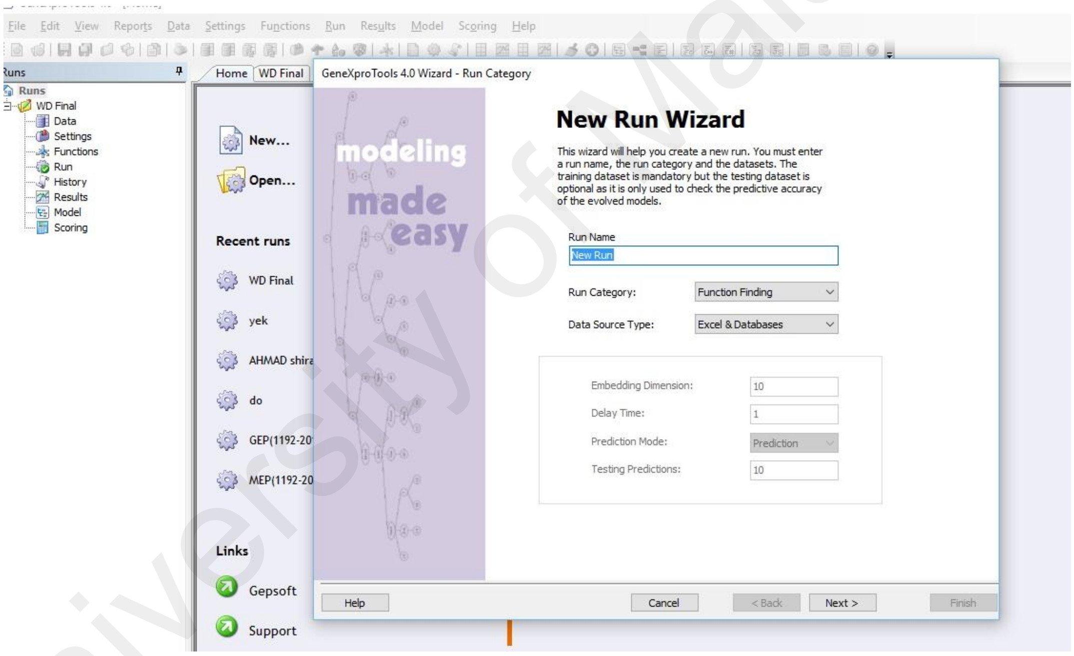
Moein Azadikhah: including on-time delivery and flexibility in giving discount to the list of the attributes of the economic aspect.

Note that the other experts agreed with the content of the questionnaire.

APPENDIX E: THE PICTURES OF EACH PART OF GENXPRO TOOLS 4.00

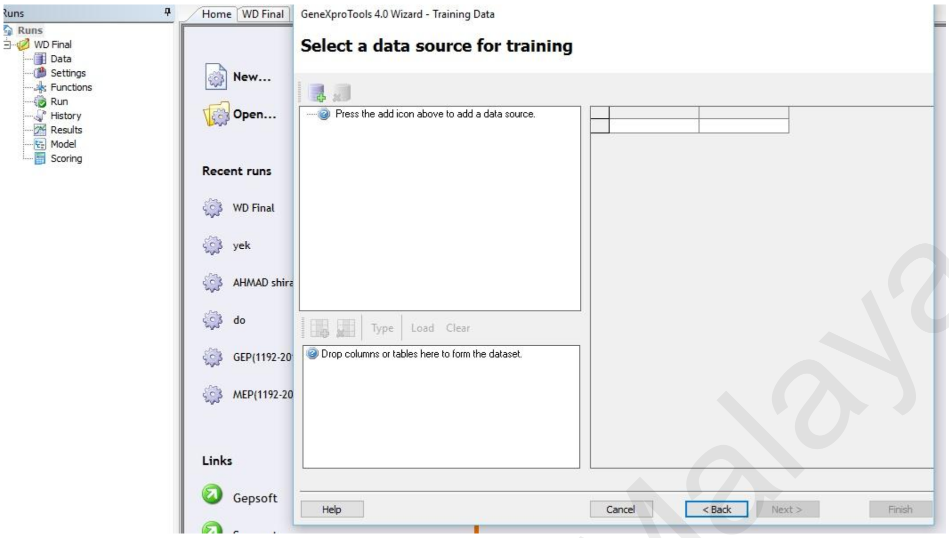
The page related to new run

This wizard helps you to create a new run. You must select the run name, run category and data sets. Note that GeneXproTools 4.0 allows you to work either with databases/Excel or text files and, for text files, accepts two different data matrix formats.



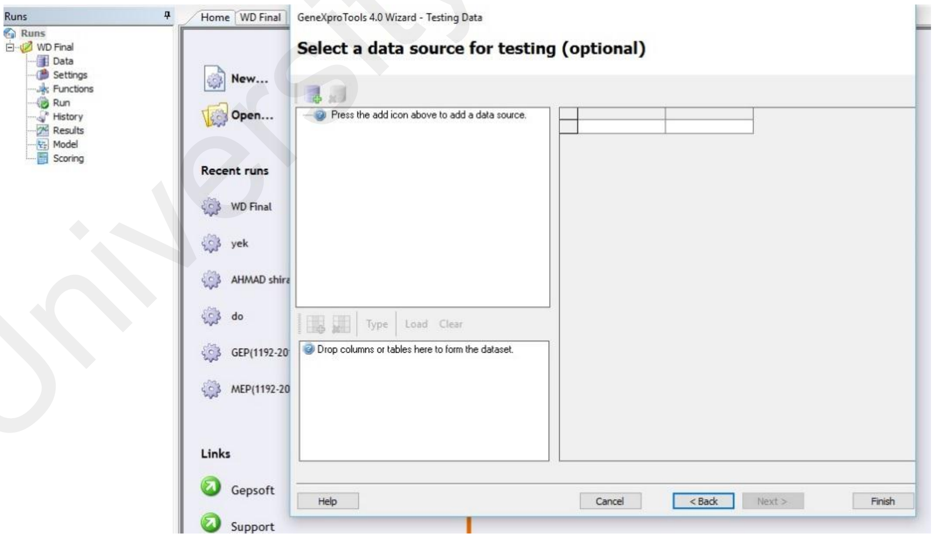
The page related to selecting the data set for training

The training data set is mandatory. Indeed, by applying this data set the model is evolved.



The page related to selecting the data set for testing

The testing data set is used for showing the predictive accuracy of the generated model.

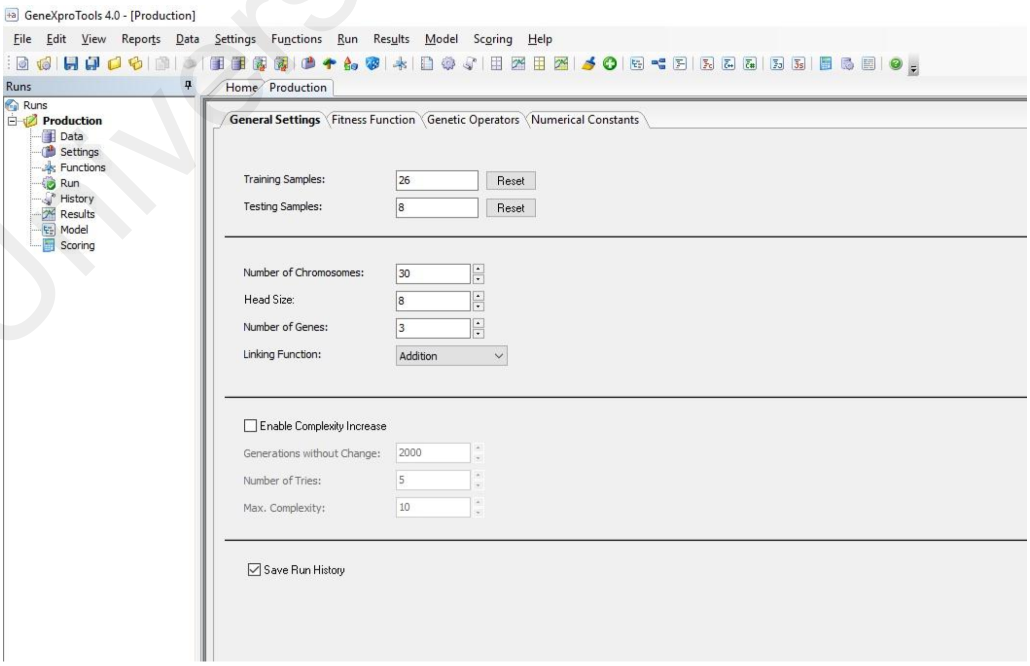


The page related to setting

This section is used for structuring the GEP-model in training. If the obtained results in both training and testing is not good, the model can be restructured. This part includes general setting, fitness function, genetic optimum and numerical constraint.

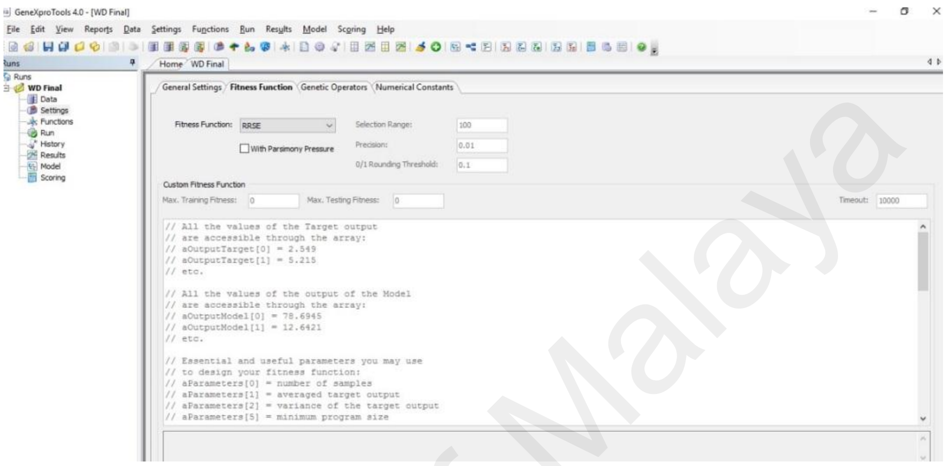
i) General setting

The page of general setting includes the head size, the number of genes and the linking function. You choose these parameters in the Settings Panel>General Settings Tab. The Head Size determines the complexity of each term in your model. The number of genes per chromosome is also an important parameter. It will determine the number of (complex) terms in your model as each gene codes for a different parse tree (sub-expression tree or sub-ET). Whenever the number of genes is greater than one, you must also choose a suitable linking function for linking the mathematical terms encoded in each gene. GeneXproTools 4.0 allows you to choose addition, subtraction, multiplication, or division to link the sub-ETs.



ii) ***Fitness function***

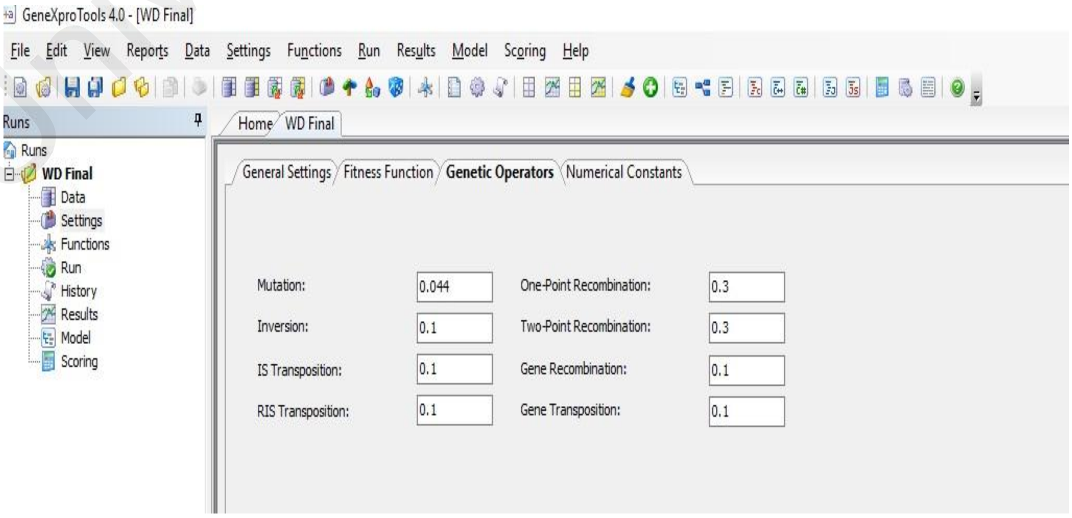
For Function Finding problems, in the Fitness Function Tab of the Settings Panel you have access to 36 built-in fitness functions. Additionally, you can also design your own custom fitness function and explore the solution space with it.



iii) ***Genetic operators***

iii.

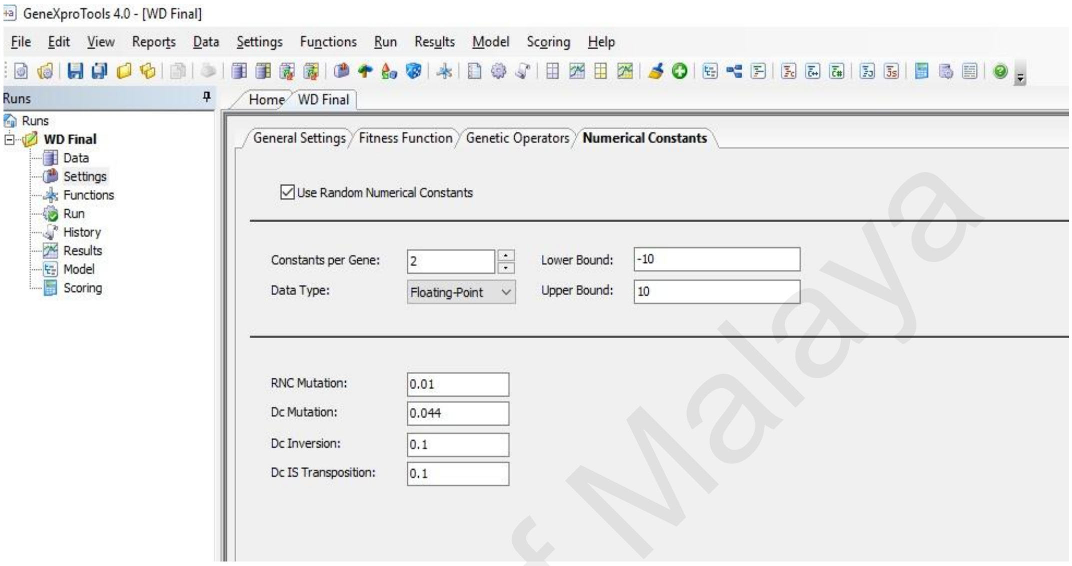
iv. This part consists of six sub-sections. It is recommended to use the default structure.



iv) The page related to numerical constant

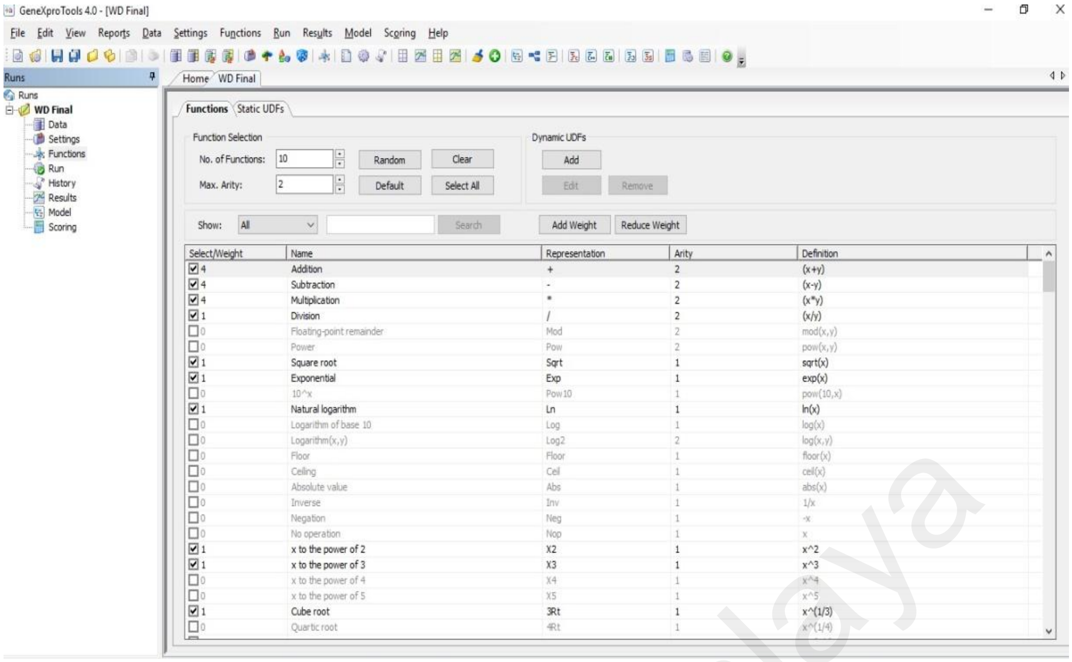
v.

vi. This section is related for times series prediction. For modeling this sub-section is not used.



The page related to the function selection page

This page includes different type of mathematical functions. This wide set of mathematical functions allows the evolution of complex and rigorous models quickly built with the most appropriate functions. The Function Selection Tool of GeneXproTools 4.0 helps you selecting different function sets very quickly through the combination of the Show options with the Random/Default/Clear/Select All buttons plus the Increase/Reduce Weight buttons in the Functions Panel.



The page related to the run page

The Run Panel allows you to control and monitor the modeling process and gives access to the following settings and features:

Evolve Button

Starts the evolutionary process from scratch, that is, from a completely random initial population.

Stop Button

Stops the evolutionary process.

Optimize Button

Starts the evolutionary process with a seed model, using it to breed better models.

Simplify Button

Also starts an evolutionary process with a seed model, but applies parsimony pressure to design more compact solutions.

Best of Run – Training

Under this heading are shown the values of Fitness, R-square, and Max. Fitness obtained on the training set for the best model of each run. These values are only updated at the end of each run or between Complexity Increase cycles. They are also updated if some relevant setting is changed, say, a different fitness function, a different training set, or a different model introduced through the Change Seed window, and if the model is afterwards processed in the Results Panel.

Best of Run – Testing

Under this heading are shown the values of Fitness, R-square, and Max. Fitness obtained on the testing set for the best model of each run. These values are only updated at the end of each run or between Complexity Increase cycles. They are also updated if some relevant setting is changed, say, a different fitness function, a different testing set, or a different model introduced through the Change Seed window, and if the model is afterwards processed in the Results Panel. If no testing set is used, a dash is shown in all the boxes.

Generation

Updates the generation number throughout a run.

Best Fitness

Updates the best fitness of each generation throughout a run.

R-square

Updates the R-square of the best-of-generation model throughout a run.

Max. Fitness

Shows the value of maximum fitness for the current run.

Program Size

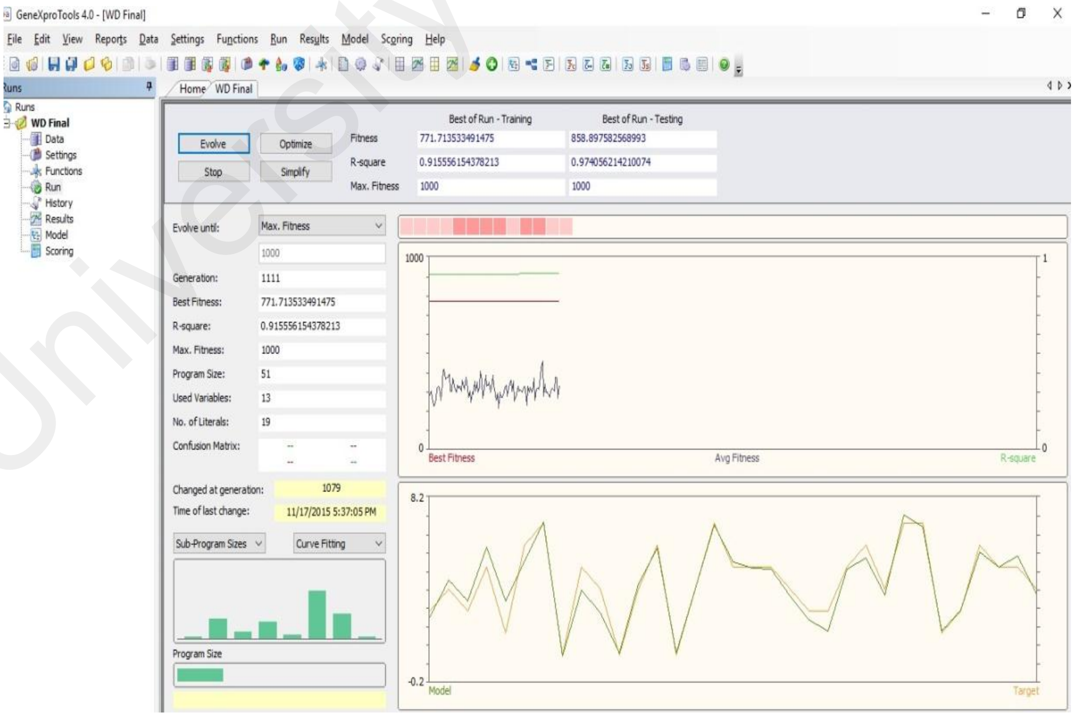
Updates the program size of the best-of-generation model throughout a run.

Confusion Matrix

This box is specific of Classification problems, and therefore only dashes are shown in Function Finding.

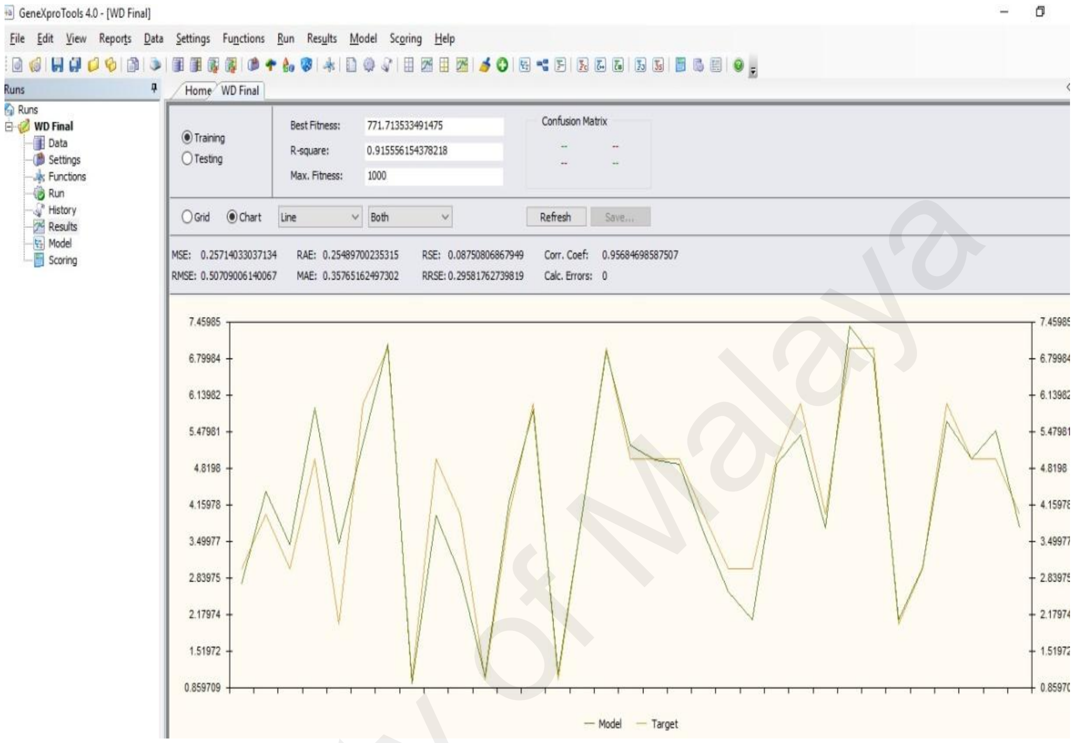
Time of Last Change

Updates, throughout a run, the time when a change in best fitness occurred.



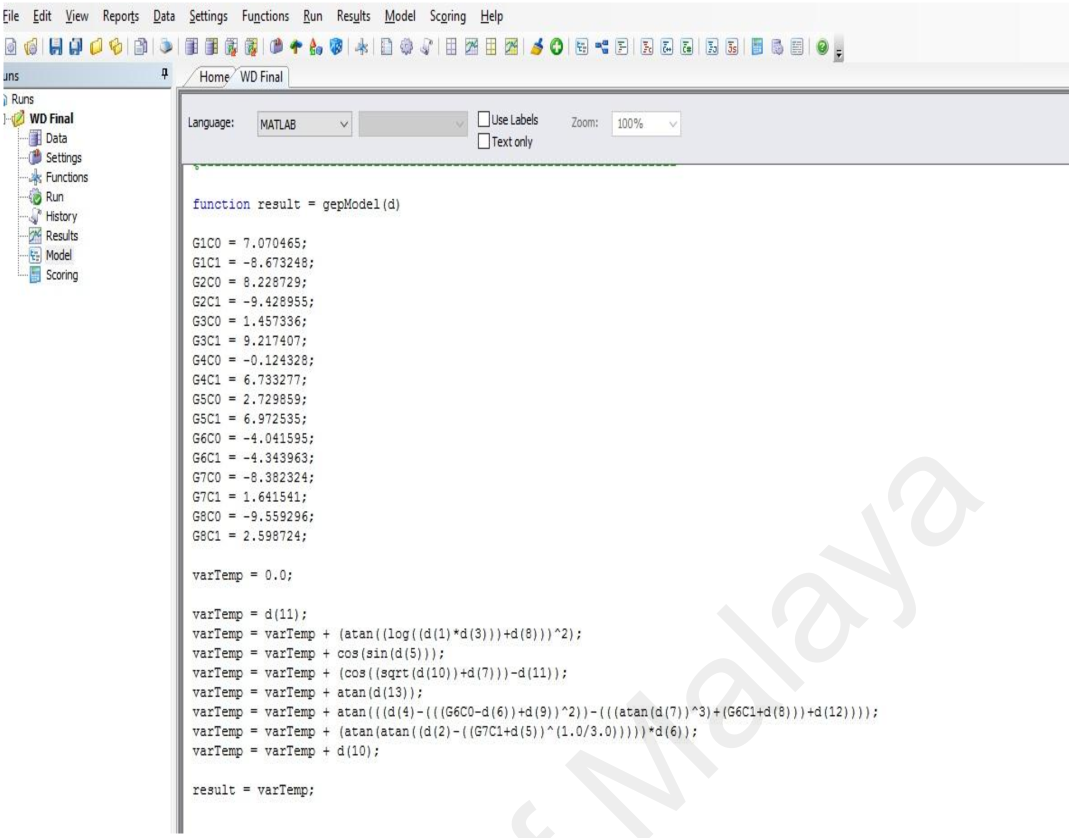
The page related to the results page

This page shows you the results obtained from training and testing. This section enables you to evaluate the developed model both in training and testing based on MSE, RMSE, RAE, R-Square etc.



The page related to the model page

The Model Page allows you to see the structure of your models and translate them into a wide range of programming languages. It gives access to the following computer codes: Karva code is saved as .txt, Ada code as .ada, C code as .c, C++ code as .hpp, C# code as .cs, Fortran code as .f, Java code as .java, Java Script code as .js, Matlab code as .m, Pascal code as .pas, Perl code as .pl, PHP code as .php, Python code as .py, Visual Basic code as .bas, VB.Net code as .vb, and VHDL code as .vhd. Note that in this research we used the MATLAB code.


File Edit View Reports Data Settings Functions Run Results Model Scoring Help
Home
WD Final
Runs
WD Final
Data
Settings
Functions
Run
History
Results
Model
Scoring
Language:
MATLAB
Use Labels
Text only
Zoom:
100%
function result = gepModel(d)
G1C0 = 7.070465;
G1C1 = -8.673248;
G2C0 = 8.228729;
G2C1 = -9.428955;
G3C0 = 1.457336;
G3C1 = 9.217407;
G4C0 = -0.124328;
G4C1 = 6.733277;
G5C0 = 2.729859;
G5C1 = 6.972535;
G6C0 = -4.041595;
G6C1 = -4.343963;
G7C0 = -8.382324;
G7C1 = 1.641541;
G8C0 = -9.559296;
G8C1 = 2.598724;
varTemp = 0.0;
varTemp = d(11);
varTemp = varTemp + (atan((log((d(1)*d(3)))+d(8)))^2);
varTemp = varTemp + cos(sin(d(5)));
varTemp = varTemp + (cos((sqrt(d(10))+d(7)))-d(11));
varTemp = varTemp + atan(d(13));
varTemp = varTemp + atan(((d(4)-(((G6C0-d(6))+d(9))^2))-(((atan(d(7))^3)+(G6C1+d(8)))+d(12))));
varTemp = varTemp + (atan(atan((d(2)-((G7C1+d(5))^(1.0/3.0)))))*d(6));
varTemp = varTemp + d(10);
result = varTemp;